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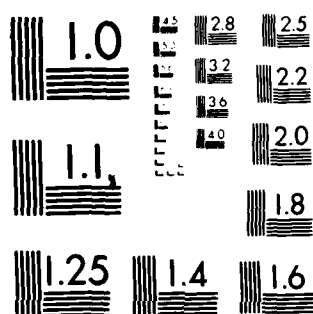
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MODULAR COMPUTING NETWORKS:
A NEW METHODOLOGY FOR ANALYSIS AND
DESIGN OF PARALLEL ALGORITHMS/
ARCHITECTURES

HANOCH LEV-ARI

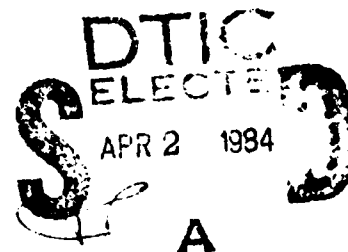
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ISI REPORT 29 • DECEMBER 1983

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SECTION 1
INTRODUCTION



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Several methods for modeling and analysis of parallel algorithms and architectures have been proposed in the recent years. These include recursion-type methods, like recursion equations, z-transform descriptions and 'do-loops' in high-level programming languages, and precedence-graph-type methods like data-flow graphs (marked graphs) and related Petri-net derived models, [1], [2]. Most efforts have been recently directed towards developing methodologies for structured parallel algorithms and architectures and, in particular, for systolic-array-like systems [3]-[10]. Some important properties of parallel algorithms have been identified in the process of this research effort. These include executability (the absence of deadlocks), pipelinability, regularity of structure, locality of interconnections, and dimensionality. The research has also demonstrated the feasibility of multirate systolic arrays with different rates of data propagation along different directions in the array.

The methodologies mentioned above provide some assistance in the analysis and synthesis of parallel algorithms and architectures, but none of them is flexible enough to address the wide scope of problems that arise in this fast developing discipline. In particular, none of these methodologies is capable of clearly displaying the multiplicity of choices for implementing a given set of recursion equations. Recent research has vividly demonstrated this multiplicity by presenting several distinct architectures for the same operation (e.g., matrix multiplication [4], [5], [7], [10]).

In this paper we present a new methodology for modeling and analysis of parallel algorithms and architectures. Our methodology provides a unified conceptual framework that clearly displays the key properties of parallel systems. In particular,

- (1) Executability of algorithms is easily verified.

- (2) Schedules of execution are easily determined. This allows for simple evaluation of throughput rates and execution delays.
- (3) Both synchronous and asynchronous (self-timed) modes of execution can be handled with the same techniques.
- (4) Algorithms are directly mappable into architectures. No elaborate hardware compilation is required.
- (5) The description of a parallel algorithm is independent of its implementation. All possible choices of hardware implementation are evident from the description of a given algorithm. The equivalence of existing implementations can be readily demonstrated.
- (6) Both regular and irregular algorithms can be modeled. Models of regular algorithms are significantly simpler to analyze, since they inherit the regularity of the underlying problem.

Ths
Our methodology is largely based upon the theory of directed graphs and can, therefore, be expressed both informally, in pictorial fashion, and formally, in the language of precedence relations and composition of functions. This duality will, hopefully, help to bridge the gap between the two schools of research in this field.

SECTION 2

MODELING PARALLEL ALGORITHMS AND ARCHITECTURES

The concepts of 'algorithm' and 'architecture,' which have been widely used for several decades, still seem to defy a formal definition. Books on computation and algorithms either take these concepts for granted or provide a sketchy definition using such broad terms as 'precise prescription,' 'computing agent,' 'well-understood instructions,' 'finite effort' and so forth. The purpose of this section is to provide a simple formal model for modeling and analysis of (parallel) algorithms and architectures. This model, which we call modular computing network (MCN) exhibits all the properties usually attributed both to algorithms and to hardware architectures. As a first step toward the formal introduction of this model we extract in Section 2.1 the main attributes of algorithms from their characterizations in the literature. This analysis of literature leads to the conclusion that algorithms can only be defined in a hierarchical manner, i.e., as well-formed compositions of simpler algorithms, and that the simplest (non-decomposable algorithms) cannot and need not be defined. The building blocks of the theory of algorithms are characterized in terms of three attributes: Function (what building blocks do), execution time (how long they do it), and complexity (what does it cost to use them). These observations are incorporated into the modular computing network model, as described in Sections 2.2 - 2.5.

2.1 TOWARD A FORMAL DEFINITION OF ALGORITHMS AND ARCHITECTURES

In this section we attempt to extract the main attributes of algorithms and architectures from a randomly chosen sample of 'definitions.' Most characterizations of algorithms are geared to the notion of sequential execution. Nevertheless, we shall see that this underlying assumption is

almost never made explicit. As a result, the attributes of parallel algorithms are, in fact, included in the available characterizations.

As a typical example consider the following definition. 'The term 'algorithm' in mathematics is taken to mean a computational process, carried out according to a precise prescription and leading from given objects, which may be permitted to vary, to a sought-for result' [11]. This definition simply states that an algorithm is a well-defined input-output map and that its domain contains at least one element, and usually more than one. However, the term 'computational process' hints that an algorithm is more than just a well-defined function. Indeed, 'A function is simply a relationship between the members of one set and those of another. An algorithm, on the other hand, is a procedure for evaluating a function' [12].

But how are functions evaluated? We are told that 'this evaluation is to be carried out by some sort of computing agent, which may be human, mechanical, electronic, or whatever' [12]. Thus, the emphasis is on physical realizability (the existence of a 'computing agent') but not on the actual details of the realization. The first axiom of the theory of algorithms is, therefore:

There exist basic functions that are physically realizable.

Further efforts to define physical realizability turn out to be quite futile. This is recognized by Aho, Hopcroft and Ullman who say, 'each instruction of an algorithm must have a 'clear meaning' and must be executable with a 'finite amount of effort.' Now what is clear to one person may not be clear to another, and it is often difficult to prove rigorously that an instruction can be carried out in a finite amount of time' [13]. Physical realizability is a matter of technology: What is non-realizable today may become realizable in a year or two. The theory of algorithms has to assume the existence of realizable basic input-output maps but need not be concerned with the details of their implementation. Therefore, the core of any theory of algorithms is a non-empty collection of undefined objects, which we shall call processors. These are the 'computing agents' mentioned above, and they are assumed to have three attributes:

- (i) Function (an input-output map)
- (ii) Complexity measure
- (iii) Execution time

A processor is assumed to be capable of evaluating the input-output map in the specified execution time. The cost of utilizing the processor is specified by its complexity measure. Notice that the notion of 'effort' mentioned above is a combination of the processor's complexity and its execution time.

It is important to draw a distinction between an algorithm and its description. An algorithm consists of processors (or basic functions), corresponding to all the functions that need to be evaluated. For instance, the computation of $\sin x$ via the first 100 terms of its MacLaurin series requires 100 basic functions, one for each term of the truncated series. The description of the same algorithm in terms of instructions requires only one instruction, which will be repeated 100 times with varying coefficients. Since descriptions of algorithms need to be communicated, stored and implemented, they must be finite, i.e., contain a finite number of instructions. The algorithm itself, on the other hand, may consist of an infinite number of processors, and used to process an infinite number of inputs into an infinite number of outputs. Such are, for instance, most signal processing algorithms: Their inputs and outputs are time-series which may, in principle, be infinitely long. The executability of these algorithms depends upon their capability to compute any specific output with finite time and effort, and to use only a finite number of inputs for this purpose. This observation also sheds a new light on the concept of 'termination,' which is usually overemphasized in definitions of algorithms.

The basic functions comprising an algorithm are interdependent in the sense that the outputs of one processor may serve as inputs to other processors. A complete characterization of an algorithm requires, therefore, to specify both its basic operations and the interconnection between these operations. The same statement applies, of course, to block-diagram representations of hardware, to flow-graphs and, in fact, to any network-type schematic. While algorithms are commonly described in some

formal language, they can also be described in a schematic manner. Conversely, schematic hardware descriptions can be transformed into formal language representations. To emphasize this equivalence we shall introduce the concept of a modular computing network (MCN), which exhibits the common attributes of both algorithms and architectures. Thus, an MCN is a pair

$$M = \{\mathcal{F}, \mathcal{G}\}$$

where \mathcal{F} , the function of the network, is essentially the collection of basic functions discussed above, and \mathcal{G} , the architecture of the network, is a directed graph describing the interconnections between basic functions. A detailed definition is provided in Section 2.1.

The concept of modular computing network is hierarchical by nature. Basic functions can be themselves characterized as networks of even more basic functions. This requires every MCN to have the three fundamental attributes of a basic function: Input-output map, complexity and execution time. We shall show in the sequel how to uniquely associate such attributes with modular computing networks. The theory of MCNs is, in short, the theory of network composition (deducing the properties of a network from its components) and network decomposition (characterizing the components and structure of a network whose composite properties have been specified).

2.2 MODULAR COMPUTING NETWORKS

A modular computing network (MCN) is a system of interconnected modules. The structural information about the network is conveyed by specifying the interconnections between the modules, most conveniently in the form of a directed graph (Figure 2-1). The functional information about the network is conveyed by characterizing the information transferred between modules and the processing of this information as it passes through the modules.

The structural attributes of an MCN are completely specified by its architecture, which is an ordered quadruple

$$\text{Architecture} = (S, T, A, P) \quad (2.2)$$

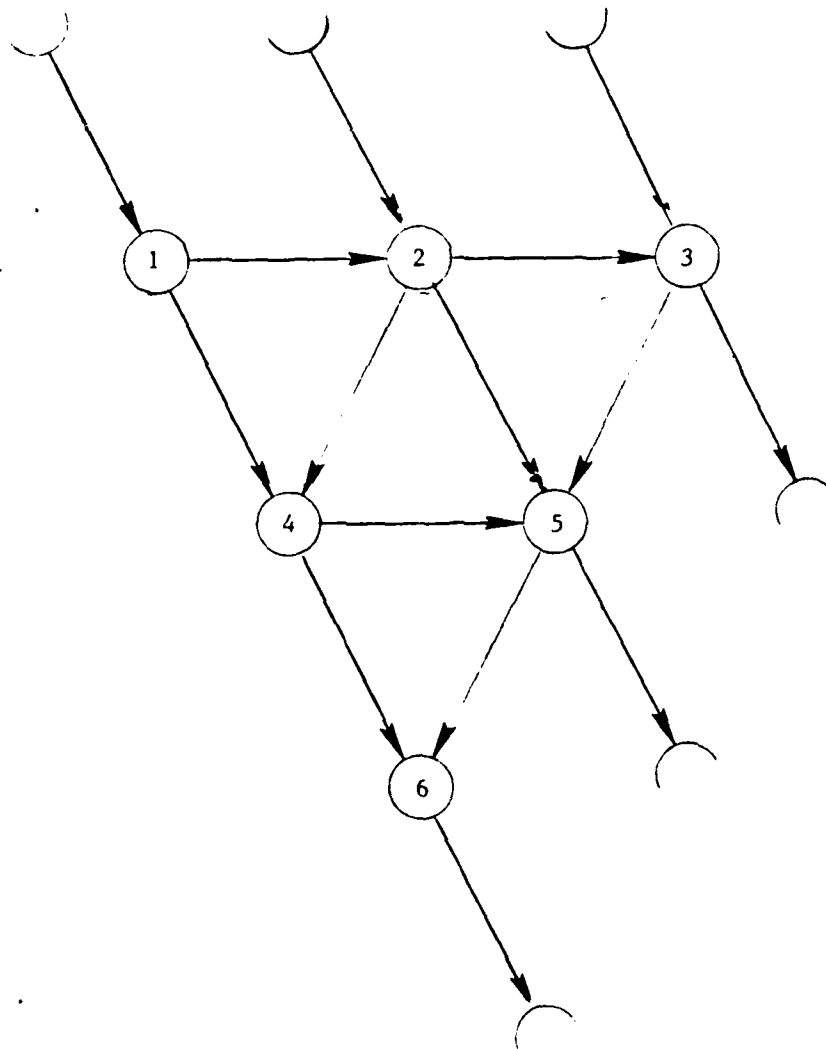


Figure 2-1. The Directed Graph Associated with a Modular Computing Network

where S, T are sets whose elements are called sources and sinks, respectively, and A, P are relations between these sets.

The ancestry relation A specifies the connections of sources to sinks. The elements of A , which are called arcs, are ordered source-sink pairs

$$a \in A \Rightarrow a = (s, t), \quad s \in S, \quad t \in T \quad (2.3)$$

An arc represents a direct transfer of information from source to sink. Two basic assumptions govern this transfer:

- (1) There are no dangling sources. Every source is connected to exactly one sink.
- (2) There are no dangling sinks. Every sink is connected to exactly one source.

These assumptions mean that the three sets S, T, A have an equal number of elements, and that the ancestry relation A establishes a one-to-one correspondence between arcs, sources and sinks, viz.,

$$(s, t) \in A \Leftrightarrow s = A(t) \Leftrightarrow t = A^{-1}(s) \quad (2.4)$$

This one-to-one correspondence will permit us to identify in the sequel each arc with its associated source and sink, and to eliminate almost all sinks and sources from the description of network architectures.

The processing relation P specifies the processing of information extracted from sinks into transformed information, which is re-injected into sources. The elements of P , which are called processors, are ordered pairs of non-empty finite sink-source sequences, viz.,

$$p \in P \Rightarrow p = \{t_1, t_2, \dots, t_m; s_1, s_2, \dots, s_n\} \quad (2.5)$$

$$t_i \in T, \quad s_i \in S, \quad 1 \leq m, n < \infty$$

The input set (t_1, t_2, \dots, t_m) consists of all the sinks from which the processor p extracts information. The transformed information is distributed among the members of the output set (s_1, s_2, \dots, s_n) . The one-to-one correspondence between sources, sinks and arcs allows us to describe processor inputs and outputs in terms of arcs and to almost completely eliminate the notion of sources and sinks. The set of input arcs of a processor p is denoted by $A_i(p)$, and the set of output arcs from the same processor is denoted by $A_o(p)$. Each processor is assumed to have unique inputs and outputs, namely

$$p, q \in P, \quad p \neq q \implies \begin{cases} A_i(p) \cap A_i(q) = \emptyset \\ A_o(p) \cap A_o(q) = \emptyset \end{cases} \quad (2.6)$$

Similarly, every collection of processors, $Q \subset P$, has its uniquely defined inputs and outputs, viz.,

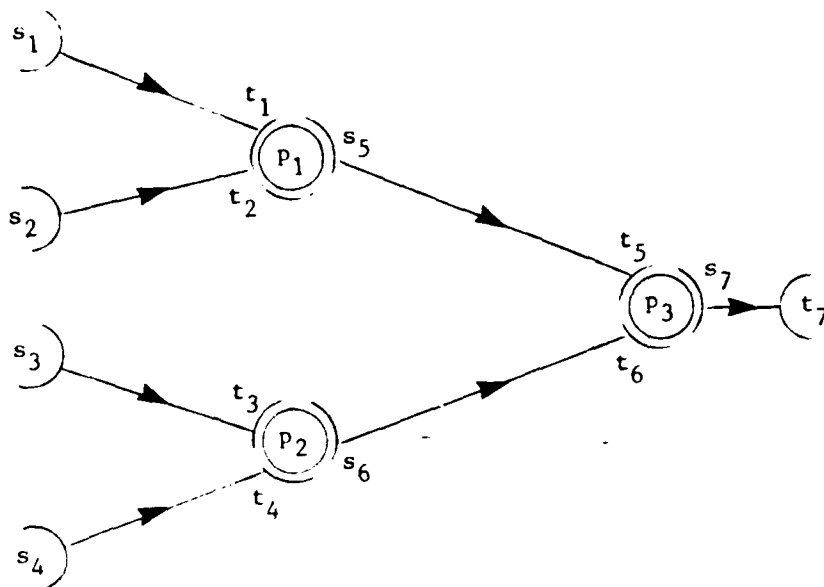
$$A_i(Q) := \bigcup_{p \in Q} A_i(p) - \bigcup_{p \in Q} A_o(p) \quad (2.7a)$$

and

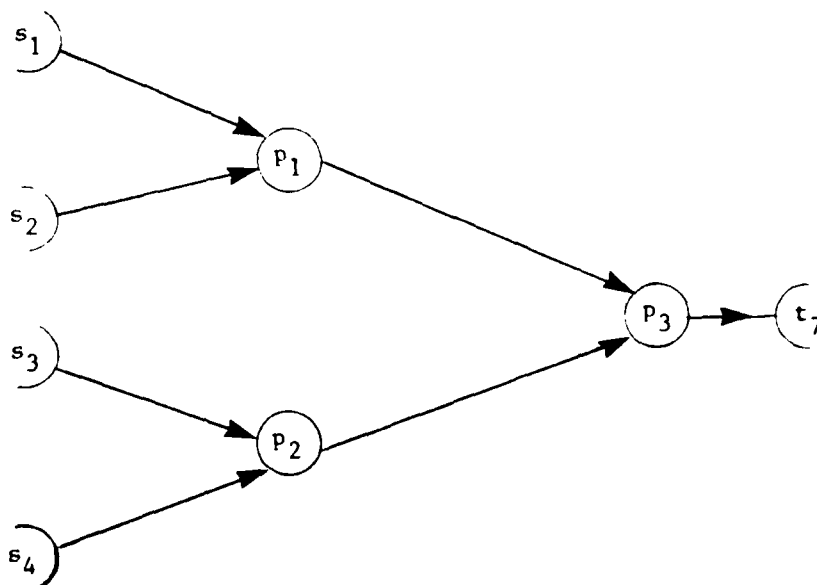
$$A_o(Q) := \bigcup_{p \in Q} A_o(p) - \bigcup_{p \in Q} A_i(p) \quad (2.7b)$$

In other words, the inputs of Q are those inputs of processors in Q that are not connected to outputs of processors in Q . A similar statement holds for outputs of Q . In particular, $A_i(P)$, $A_o(P)$ are the inputs and outputs of the entire network.

Network architectures are most conveniently described by a directed graph that combines together the ancestry relation A and the processing relation P into a single block-diagram-like representation (Figure 2-2a). Sources and sinks are denoted by semi-circles, processors by circles and arcs are, obviously, denoted by arcs. Sources and sinks are paired, and each processor has its inputs and outputs adjacent to itself. An obvious reduction in notation (Figure 2-2b) enhances the comprehensibility of the description. The reduced form is, essentially, a block-diagram representation of the network architecture, and can be interpreted as a directed graph \mathcal{G} .



a. Full Form Description



b. Reduced Form Description

Figure 2-2. Equivalent Full Form and Reduced Form Descriptions of Network Architectures

$$\mathcal{G} = \{V, A\} \quad (2.8a)$$

The set of vertices V of this graph is

$$V = \{A_i(P), P, A_o(P)\} \quad (2.8b)$$

where $A_i(P)$ are interpreted as the sources corresponding to the input arcs and $A_o(P)$ are interpreted as the sinks corresponding to the output arcs. The arcs of the directed graph coincide with the original set of arcs A . The interpretation of network architectures as directed graphs puts at our disposal the powerful tools and results of graph theory. Some of these will be used in the sequel to characterize and analyze the structure of modular computing networks.

The functional attributes of an MCN are completely determined by its architecture and by specifying the functional attributes of each processor. Thus, the function of a network is an ordered pair

$$\mathcal{F} = \{X, F\} \quad (2.9)$$

where X, F are sets whose elements are called variables and maps, respectively.

The elements of X are sets (i.e., domains) and 'assigning a value to a variable' amounts to choosing a particular element in the domain corresponding to that variable. There is one variable, x_a , associated with every arc $a \in A$ of the corresponding architecture. Consequently, there is a one-to-one correspondence between variables, sources, sinks and arcs. This correspondence makes it possible to refer to the variables associated with the inputs of a given processor p as the input variables of p and denote them by $X_i(p)$. A similar notation, $X_o(p)$, is used for the variables associated with the outputs of the processor p .

The elements of F are multivariable maps. There is one map, f_p , associated with every processor $p \in P$ of the corresponding architecture. It maps the input variables of this processor into the corresponding output variables, viz.,

$$f_p : X_i(p) \rightarrow X_o(p) \quad (2.10)$$

which means that each of the output variables is a function of the input variables (not necessarily of all the input variables). This establishes a precedence relation between the inputs and outputs of a given processor, viz.,

$$x \rightarrow y \quad (2.11)$$

if $x \in A_i(p)$, $y \in A_o(p)$ and if y is a function of x (and, possibly, of other input variables). The transitive closure of this relation is also a precedence (i.e., a partial order): We shall say that x_1 precedes x_n if there exists a sequence of variables such that

$$x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_n$$

in the sense of (2.11). This global precedence will also be denoted by $x_1 \rightarrow x_n$. The ancestry [14] of a variable $x \in X$ is the set of all variables that precede x , viz.,

$$a(x) := \{z; z \in X, z \rightarrow x\} \quad (2.12)$$

These are all the variables that have to be known in order to determine the value of x .

Since the function of a network consisting of a single processor p is

$$\mathcal{F}_p = \{X_i(p) \cup X_o(p), f_p\}$$

there is, essentially, no distinction between the function and the map of p . Thus, the input-output map of a single processor may also be called the function of the processor. The same is not true for a network consisting of several processors: The input-output map of a network is a single multivariable map, relating the outputs of the network to its inputs; the

function of the network, in contradistinction, is the collection of the atomic maps that comprise the network. The analysis problem for computational networks is to determine the network map from its function. The synthesis problem is to design an MCN (i.e., specify its structure and function) that realizes a given multivariable input-output map.

Modular computing networks need not be finite. In fact, most signal processing algorithms correspond to infinite MCNs. However, the concept of finite effort, involved in the evaluation of variables, imposes certain constraints upon infinite networks. First, the number of inputs and outputs of every processor must be finite. This means that the graph \mathcal{G} describing the architecture is locally finite [15]. Next, every variable must be computable with finite effort, so it will be required to have a finite ancestry, viz.,

$$|a(x)| < \infty \quad \text{for all } x \in X \quad (2.13)$$

We shall also assume that the number of connected components of the architecture \mathcal{G} is countable. A modular computing network that satisfies the three assumptions stated above--local finiteness, finite ancestry and countable number of connected components--will be called structurally finite. The following result characterizes the kind of infinity allowed in such networks.

Theorem 2.1

A structurally finite MCN has a countable number of variables and processors. The following three statements are equivalent:

- (1) The number of variables is finite.
- (2) The number of output variables is finite.
- (3) The number of processors is finite.

Proof:

The countability of the variables and processors of a connected network is a direct consequence of local finiteness (see, e.g., [15]). Since each connected component has a countable number of variables and processors, the same is obviously true for a countable number of connected components. Thus the number of variables and processors of a structurally finite MCN must be countable. As a consequence of local finiteness, a finite number of processors implies a finite number of variables and vice versa, so (1) and (3) are equivalent. Clearly (1) implies (2), while (2), via the finite ancestry condition, implies (1).

2.3 CAUSALITY AND EXECUTIONS

The definition of processors in the previous section did not take into account any constraints imposed by hardware implementation considerations. the most important among these constraints is the causality property. It will be henceforth assumed that an output of a processor cannot become available before the inputs of the same processor that precede this output became available. In the beginning all variables are unavailable; the inputs of the network are made available at a given instant, and following that event, all variables of the network gradually become available. This temporally ordered process, which we shall call execution, must be consistent with the precedence relation between variables induced by the directed nature of the architecture \mathcal{G} . A network that possesses an execution in which every variable ultimately becomes available is said to be executable (or 'live' in the terminology of Petri-nets [1]). It is clear that a network containing a cycle cannot be executable since every variable (= arc) on the cycle can never become available. In order to satisfy the causality assumption every variable in the cycle must temporally precede itself (i.e., it must be available before it becomes available (Fig. 2-3)), which is, clearly, impossible. It turns out that every acyclic architecture is executable. To prove this result we shall need to formalize the notion of execution.

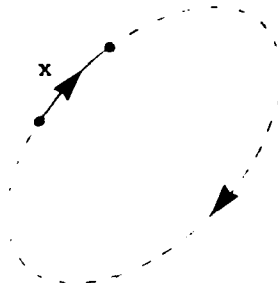


Figure 2-3.

An execution of an MCN is a partitioning of its variables into a sequence of finite disjoint sets, viz.,

$$E = \{S_i; 0 \leq i < \infty, |S_i| < \infty, S_i \cap S_j = \emptyset \text{ for } i \neq j, \bigcup S_i = X\} \quad (2.14a)$$

such that the precedence relation is preserved, viz.,

$$a(S_i) \subset \bigcup_{j=0}^{i-1} S_j \quad i = 0, 1, \dots \quad (2.14b)$$

Here $a(S)$ denotes the ancestry of the set S , defined as the collection of all ancestors of members of S , viz.,

$$a(S) := \bigcup_{x \in S} a(x) \quad (2.15)$$

In simple words, every ancestor of $x \in S_i$ must be contained in one of the sets S_0, S_1, \dots, S_{i-1} , which we shall call levels. Executions can be interpreted as multistep procedures for evaluating all the variables in X . The members of the level S_i are evaluated at the i -th step, and the

condition (2.14b) guarantees the availability of all their ancestors at the right moment. Since the ancestors of the level S_i strictly precede S_i all variables in this set can be evaluated simultaneously giving rise to a parallel execution. If each set S_i contains exactly one variable the execution will be called sequential.

Since each level S_i in an execution is finite, the evaluation of the variables in S_i from the members of the preceding levels requires finite effort. Since each variable belongs to some level S_i , the total effort involved in the evaluation of a single variable from the global inputs is also finite. Thus, the existence of an execution for a given MCN implies that every variable can be evaluated with finite time and hardware. A network that has an execution deserves, therefore, to be called executable.


The preceding discussion implies that executability is a structural property, since only the precedence relation between variables is involved in constructing executions. The following result presents a simple structural test for executability of MCNs.

Theorem 2.2

A structurally finite MCN is executable if, and only if, its architecture is acyclic.

Proof:

If an execution exists, then it can be easily converted into a sequential execution by ordering the variables in each (finite) level S_i in some arbitrary manner. Thus, executability is equivalent to the existence of a sequential execution. By a well-known result in the theory of finite directed graphs, a sequential ordering exists if, and only if, the graph is acyclic. Thus, the theorem holds for finite MCNs. The proof for infinite networks is given in Appendix A.



Corollary 2.2

Executable MCNs always have sequential executions.

The corollary confirms the intuitive notion of executability: Any computation that can be carried out in parallel can also be carried out sequentially. Parallel execution offers, however, an attractive trade-off between hardware and time, which will be discussed in detail in Sec. 3.4.

Theorem 2.2 provides a simple test for executability and, in effect, prevents the construction of non-executable MCNs. Thus, the pitfalls of starvation and deadlocks, well known in the context of Petri-nets [1] are easy to avoid. Notice also that since each variable in an MCN is evaluated exactly once, safeness [1] is guaranteed. This means that inputs to processors do not disappear before they have been used to evaluate the subsequent outputs. Safeness is achieved because once a variable becomes available it stays so forever, and never disappears.

2.4 HIERARCHICAL COMPOSITION OF MCNs

Modular computing networks are, by definition, constructed in a hierarchical manner. A processor p in an MCN can itself be a network, provided it has a well defined input-output map f_p . In this section we analyze the constraints that have to be imposed upon MCN composition in order to guarantee the existence of a well-defined global input-output map.

From the structural point of view a composition is simply a network of networks. The 'processors' of the composite network are MCNs and the arcs represent interconnections between outputs of MCNs to inputs of other MCNs. The architecture of the composition, obtained by regarding each MCN component as a simple 'processor' has to satisfy the constraints of Sec. 2.2. An architecture is called admissible if it satisfies the three following constraints:

- (1) No dangling inputs and outputs
- (2) No cycles
- (3) It is structurally finite

The importance of these constraints lies in the fact that an admissible composition of admissible architectures is itself an admissible architecture (see Appendix B for proof). It is interesting to notice that the admissibility conditions are instrumental also in establishing other important properties of architectures. In particular, an admissible composition of self-timed elements is itself a self-timed element [6], [7].

To establish the hierarchical nature of composition it is only necessary to verify that an admissible composition of processors with a well-defined input-output map also has a well defined input-output map. This will be done by interpreting executions as decompositions of MCNs into elementary parallel and sequential combinations.

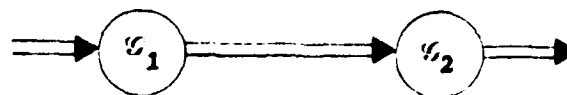
Parallel composition of two architectures, \mathcal{G}_1 and \mathcal{G}_2 , is defined as the union of the two networks without any interconnections between \mathcal{G}_1 and \mathcal{G}_2 (Fig. 2-4a). Sequential composition involves the connection of every output of \mathcal{G}_1 to a corresponding input of \mathcal{G}_2 ; thus the number of outputs of \mathcal{G}_1 must equal the number of inputs of \mathcal{G}_2 (Fig. 4-2b). We shall denote parallel composition by $\mathcal{G}_1 \# \mathcal{G}_2$ and sequential composition by $\mathcal{G}_1 * \mathcal{G}_2$. The parallel composition of a countable number of admissible networks is always admissible. The sequential composition of a sequence of admissible networks is admissible too, i.e.,

$$\mathcal{G}_1 * \mathcal{G}_2 * \dots$$

is admissible because the unilateral nature of the cascade preserves the finite ancestry property, while local-finiteness and countability of components are clearly preserved.



a. Parallel Composition $S_1 \# S_2$



b. Sequential Composition $S_1 \circ S_2$

Figure 2-4. Fundamental Architecture Compositions

Executions define a rearrangement of MCNs as a sequential composition of subnetworks, each subnetwork being a parallel composition of processors. The MCN of Figure 2-1 can, for instance, be described as

$$(f_1 \# e \# e) * (e \# f_2 \# e) * (f_4 \# e \# f_3) * (e \# f_5 \# e) * (f_6 \# e \# e)$$

where e is an identity input-output map. The importance of this observation lies in the fact that the input-output map of any sequential-parallel composition is well-defined. Consequently, every execution has a well-defined input-output map. This leads to the following result.

Theorem 2.3

Every executable MCN has a unique well-defined input-output map.

Proof:

See Appendix C.

The theorem establishes the utility of the notion of execution. While each execution corresponds to a different ordering of the computations required to evaluate the output variables of an MCN, all executions determine the same input-output map. And, while each execution provides a different description of the network, they all correspond to the same MCN.

Descriptions of computational schemes will be considered equivalent if they determine the same input-output map. They will be considered structurally equivalent if, in addition, they determine the same MCN. Structural equivalence, which amounts to different choices of executions, leaves both the architecture and the function of the MCN unchanged. Other types of equivalence transformations will affect both the architecture and the function of the MCN but will keep its input-output map unchanged.

2.5 COMPARISON OF MCNs WITH OTHER NETWORK MODELS

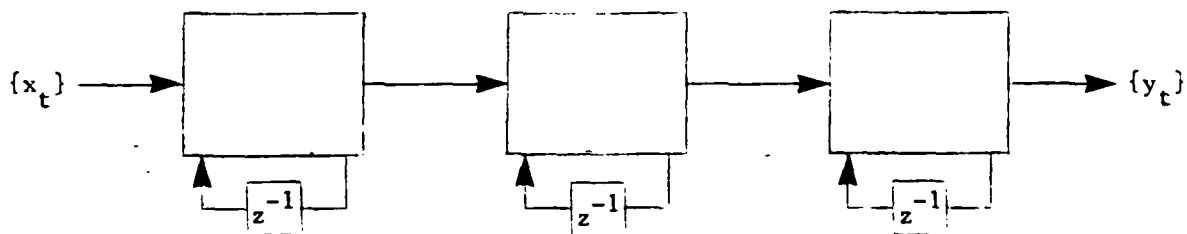
2.5.1 Block-Diagrams and Finite-State Machines

Numerical algorithms are most frequently described in terms of recursion equations involving indexed quantities, known as signals. Z-transform notation and block diagrams (or signal-flow-graphs) are sometimes used as equivalent descriptions of recursion equations.

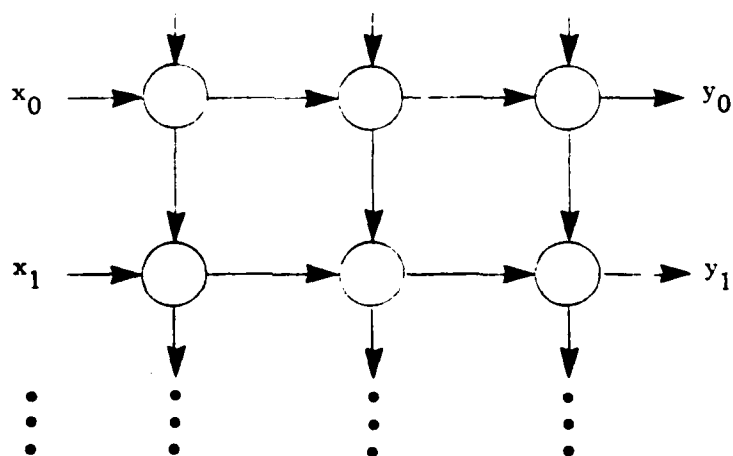
The main difference between MCNs and Z-transform block-diagrams is in the distinguished role of time in the latter model. A cascade connection of three blocks, each with its own state (Fig. 2-5a) corresponds to an MCN of infinite length (Fig. 2-5b). Each row of the MCN represents a single step of the recursion. Each input/output is a single variable, not a time-series. While the MCN description seems wasteful, it does in fact enhance our understanding of the various possibilities of implementation. Moreover, MCNs can describe irregular algorithms that cannot be described in terms of recurrence equations. This means that every block diagram can be converted into an MCN but not vice versa. The conversion amounts to duplicating the block diagram several times (once for every iteration of the recursion) and converting delay elements into direct connections between consecutive duplicates, as in Figure 2-5.

The preceding discussion considered only block-diagrams that correspond to sets of recursion equations. Such diagrams always consist of delay elements and memoryless operations. This means, of course, that only block-diagrams whose blocks represent finite-state machines can be converted in a straightforward manner into an MCN. Any other block-diagram has to be first converted into a state-space form (i.e., every block has to be represented by a state-space model or a combination of such models) before it can be converted into an MCN. Thus, in particular, any signal-flow-graph with rational transfer functions can be transformed into an MCN.

The correspondence between block-diagrams and MCNs provide a simple test for the executability (= computability) of algorithms represented by block diagrams.



a. Block-Diagram



b. Modular Computing Network

Figure 2-5. The Correspondence Between Block-Diagrams and MCNs

Executability Test

A finite block-diagram (or signal-flow-graph) whose blocks are characterized by delay elements and memoryless maps is executable if, and only if, the directed graph obtained by deleting delay elements from the diagram (or equivalently, by setting $z^{-1} = 0$ in the transfer functions) is acyclic.

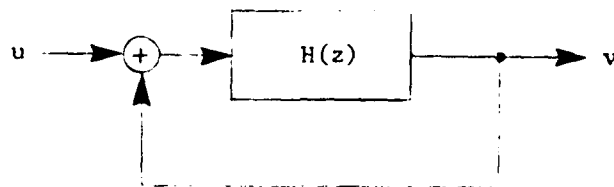
Proof:

Since delay elements are causal, they can never give rise to cycles in the corresponding MCN. In other words, since all operations in the i -th iteration temporally precede all operations in the $(i+1)$ -th iteration, the only cycles the MCN representation of a block-diagram may have must be contained within a single layer, corresponding to a single iteration. A single layer of the MCN is obtained by removing all delay elements from the block-diagram.

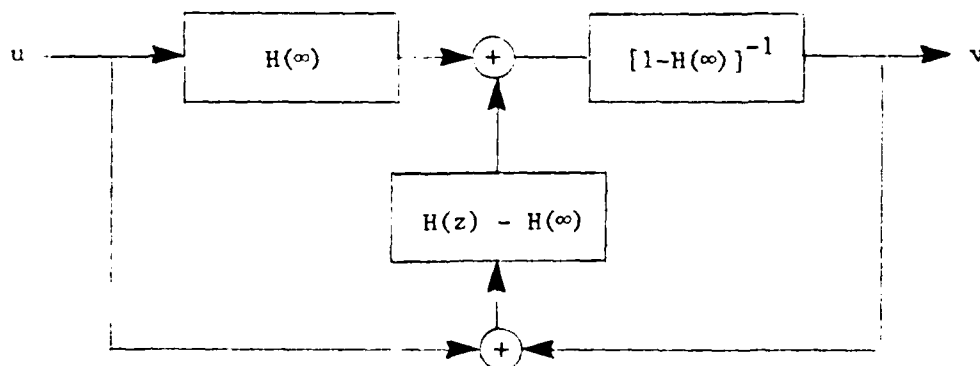
The test not only establishes the executability of a given block-diagram but indicates how to transform non-executable networks into executable ones. Consider, for instance, the network in Figure 2-6a. It is non-executable if $H(\infty) \neq 0$, because a cycle exists in the network for $z = \infty$. However, the same transfer function can be realized by the network in Figure 2-6b, which is executable.

2.5.2 Data-Flow-Graphs and Petri-Nets

The MCN is, clearly, a data-flow-graph [18] with the additional constraint that only one token is placed at every input of the network, and consequently, only one token eventually appears at every output of every processor. Thus, an MCN is safe by definition. In spite of this



a. Non-Executable Network



b. Equivalent Executable Network

Figure 2-6. Transformation of a Non-Executable Network into an Equivalent Executable One

observation every data-flow-graph (safe or unsafe) can be converted into an MCN, as long as every firing of a vertex in the flow-graph removes one token from every input line and adds one token to every output line. This constraint implies that the data-flow-graph can be converted into a block diagram involving only delay elements, advance elements and memoryless maps. This block-diagram can in turn be converted into a (not necessarily executable) MCN. The executability condition, when transformed back to the data-flow-graph domain becomes a cycle sum test, as described in [19].

Petri-nets are more general than data-flow-graphs. They allow two different kinds of vertices, known as places and conditions. Conditions correspond to our concept of processors, while places are combinations of multiple sources and sinks and thus have no counterpart in the MCN model. Petri-nets whose places have at most one input and at most one output are, in fact, data-flow-graphs (also known as marked graphs [20]) and can be converted into MCNs.

2.5.3 High-Level Programming Languages

Most high-level-language computer programs can be converted with little difficulty into MCNs. Each assignment statement of the program becomes a processor in the corresponding MCN. Program variables are mapped into network variables according to the following rules:

- (i) Each program variable, say x , is mapped into several network variables, denoted by x_1, x_2 , etc.
- (ii) An occurrence of a program variable x in the right-hand-side of an assignment statement is mapped into the same network variable x_i as the preceding occurrence of the same variable in the program.
- (iii) An occurrence of a program variable x in the left-hand-side of an assignment statement is mapped into a new network variable, i.e., into x_{i+1} if the most recent occurrence was mapped into x_i .

Recursions (do-loops) are mapped into sequential compositions of identical processors, each processor corresponding to one step of the recursions. The mapping of conditional recursions ('if' and 'while' statements) is somewhat more complicated and will not be described here. A separate technical memo will be devoted to the details of converting computer programs and other descriptions into MCNs, and vice versa.

The conversion of an MCN into a computer program is straightforward: Each processor is mapped into several assignment statements, and each network variable is mapped into a program variable. As an example consider a simple computer program (Table 2-1) written as a subroutine to emphasize the role of inputs and outputs. The corresponding MCN is given by the same table, and is described graphically in Figure 2-7. Notice that the order of assignment statements of an MCN is inconsequential: Any arrangement of these statements conveys exactly the same information. Also notice that we have the option of aggregating several statements with the same inputs into one processor in order to enhance the comprehensibility of the representation. The MCN representation of Table 2-1 is, in fact, the 'computer program' equivalent of Figure 2-7, so that no translation is required once such a 'formal language' representation is available. Translation of MCNs into computer programs usually results in poor utilization of computer resources. This inefficiency can, however, be easily handled at the compiler level. On the other hand, the comprehensibility of MCN representations is much better than the average computer program.

2.5.4 Summary

The preceding analysis has shown that MCNs are essentially equivalent to computer programs, to block diagrams involving finite-state-blocks, and to a subclass of Petri-nets (marked graphs). The major distinction between MCNs and most other representations is the embedding of the notion of executability into the MCN model itself. Thus, the only way to design non-executable MCNs is by the introduction of cycles in the network architecture. Moreover, the test for executability is very easy to carry

TABLE 2-1. CONVERSION OF COMPUTER PROGRAMS INTO MCN: AND VICE VERSA

COMPUTER PROGRAM	<p>SUBROUTINE EXAMPLE (X,Y,Z,W)</p> <p>YTEM = X*Y</p> <p>X = X + Y</p> <p>ZTEM = Z*W</p> <p>W = Z + W</p> <p>Y = YTEM + ZTEM</p> <p>Z = YTEM - ZTEM</p> <p>RETURN</p> <p>END</p>
MCN REPRESENTATION	<p>MCN EXAMPLE (X1,Y1,Z1,W1;X2,Y2,Z2,W2)</p> <p>1) YTEM = X1*Y1</p> <p>X2 = X1 + Y1</p> <p>2) ZTEM = Z1*W1</p> <p>W2 = Z1 + W1</p> <p>3) Y2 = YTEM + ZTEM</p> <p>Z2 = YTEM - ZTEM</p> <p>END</p>

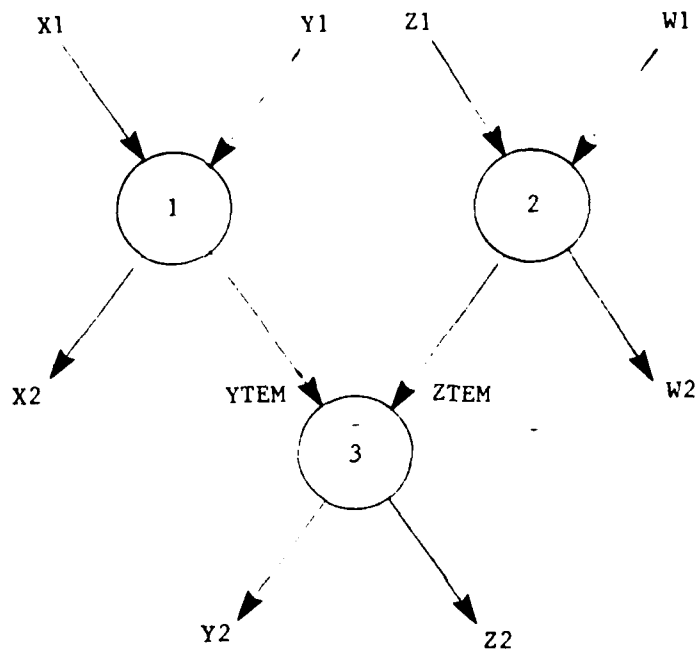


Figure 2-7. The MCN 'EXAMPLE' Corresponding to Table 2-1.

out and can be included in any compiler for MCN representations. It is much easier, on the other hand, to design malfunctioning Petri-nets or computer programs, and much more difficult to detect the errors in the design.

SECTION 3

STRUCTURAL PROPERTIES OF MCNs

The notion of execution, defined in the previous section, provides several quantitative characterizations of the MCN architecture. In particular, it can be used to number the processors of an MCN and to introduce concepts of dimensionality. A refinement of the notion of execution leads to time schedules and to the formulation of composition rules for execution times. Thus, the objective of associating a unique execution time with every output of an MCN is achieved. The third objective, that of associating a unique measure of complexity with each MCN, has yet to be accomplished. Currently there is no consensus even upon the measure of complexity for a single processor, let alone for a network of processors. Some progress has been made in characterizing complexity in terms of 'area,' but more research is required before commonly-accepted rules for composition of complexity can be formulated. For this reason the topic of complexity will not be considered in the sequel.

3.1 NUMBERING OF VARIABLES AND PROCESSORS

The concept of execution, which was defined in Section 2.3, defines a numbering $E(x)$ on the variables of an MCN, viz.,

$$x \in S_i \iff E(x) = i \quad (3.1)$$

Since the partitioning $\{S_i\}$ and the numbering $E(\)$ determine each other and convey equivalent information, we shall call the function $E(\)$ itself an execution. Several variables may share the same value of $E(\)$, which means they belong to the same level S_i . If each level of an execution contains exactly one variable the execution is called sequential. The function $E(x)$ defines, in this case, a sequential ordering of the

variables and of the processors comprising the MCN. The numbering of variables determined by an execution $E(\)$ is consistent with the precedence relation since we clearly have

$$E(x) \geq 1 + \max_y \{E(y); y \in a(x)\} \quad (3.2)$$

Similarly, we can define a numbering of the processors by

$$E(p) := \max_x \{E(x); x \in X_1(p)\} \quad (3.3)$$

The value of $E(p)$ indicates the earliest instant at which all inputs of the processor p become available. We can also define a precedence relation for processors, viz.,

$$q \rightarrow p$$

if there exists a directed path from q to p . This relation, in turn, determines the ancestry set $a(p)$ of each processor by

$$a(p) := \{q; q \in P, q \rightarrow p\} \quad (3.4)$$

It can now be seen that an analog of (3.2) holds for the numbering of processors, viz.,

$$E(p) \geq 1 + \max_q \{E(q); q \in a(p)\} \quad (3.5)$$

Since a typical MCN has fewer processors than variables, the numbering of processors is a more convenient tool for structural analysis of an MCN.

3.2 DIMENSIONALITY AND ORDER

A family of sequential executions $\{E_i(\)\}$ on a given MCN is called representative if

$$q \in \alpha(p) \Leftrightarrow E_i(q) < E_i(p), \text{ all } i \quad (3.6)$$

Notice that a representative family can never consist of a single execution (except in the case of a purely sequential MCN) because there exist always two processors q, p such that $E(q) < E(p)$ even though q does not precede p (nor does p precede q). The following result shows that every MCN has at least one representative family.

Theorem 3.1

The collection of all sequential executions of a given MCN is a representative family.

Proof:

By the definition of execution

$$q \in \alpha(p) \Rightarrow E(q) < E(p)$$

for every execution (sequential or not). To prove the converse assume that $\{E_i(\)\}$ is the collection of all sequential executions, and that for some processors p, q

$$E_i(q) < E_i(p), \text{ all } i$$

Clearly p cannot precede q , but they may be incomparable. In this case there exists a non-sequential execution $\tilde{E}(\)$ such that

$$\tilde{E}(p) = \tilde{E}(q)$$

Since every execution can be transformed into a sequential one by arbitrarily ordering the variables in each level, it follows that \tilde{E} can be converted into a sequential execution, say E_0 , such that

$$E_o(q) > E_o(p)$$

This, however, contradicts the assumptions. Hence, p, q cannot be incomparable and we must have $q \in \alpha(p)$.

A representative family with the smallest number of members will be called a basis (it need not be unique). The cardinality of bases is defined as the dimensionality of the MCN in consideration. The members of a basis $\{E_i(\)\}$ define a coordinate basis for the network, such that the coordinates of a processor p are $\{E_1(p), E_2(p), \dots, E_n(p)\}$. Notice that the dimensionality of a network is bounded below by the dimensionality of all its subnetworks, so adding long chains of processors to a 2-dimensional network cannot reduce the overall dimension below 2 (Figure 3-1).

Every basis of an MCN determines a unique non-sequential execution obtained by ordering the processors according to the sum of their basis coordinates. For the example of Figure 3-1 this execution is

$$(1), (2,3) (4) (5) \dots (n)$$

The order of a basis is defined as the number of variables in the largest layer of the parallel execution determined by the basis. For the example above the order is 2 since there is a set of 2 processors in the parallel execution. Since an MCN may have many bases it has no unique order. Moreover, each execution E (not necessarily associated with a basis) has its own order, defined by

$$\text{ord}(E) := \max_i \{p; E(p) = i\} \quad (3.7)$$

Executions can be implemented in hardware by mapping each layer into a single iteration, with all the processors in the layer implemented in parallel. The order of an execution, which is the number of processors in the largest layer, is therefore a measure of the hardware complexity of such an implementation.

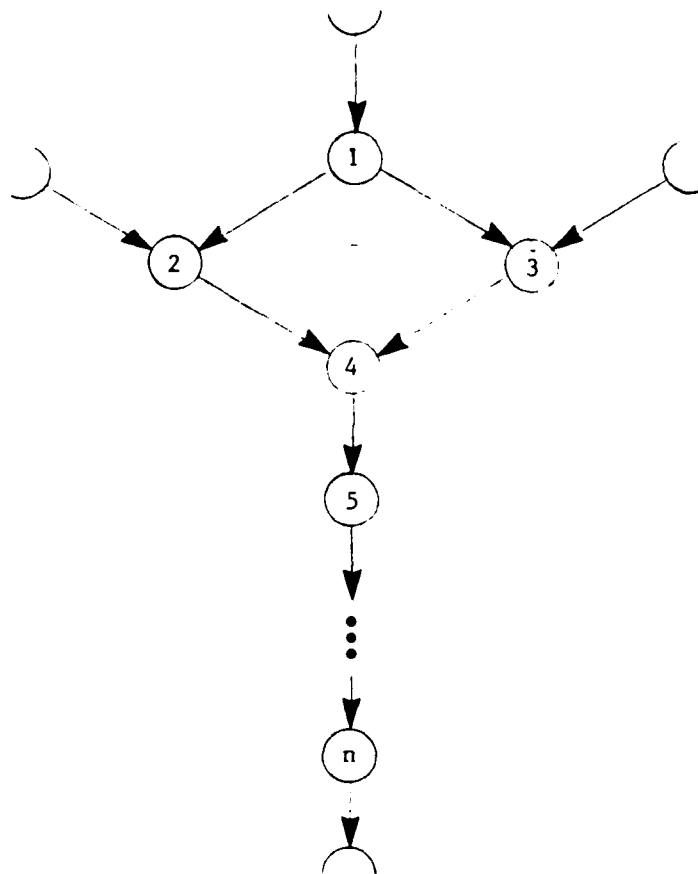


Figure 3-1. Example of a 2-D Network. The basis is formed by the executions 1,2,3,4,5,...,n and 1,3,2,4,5,...,n.

Once we have coordinate bases at our disposal we can apply metric arguments to the representation of an MCN. For instance, we can define distances between processors and introduce the concept of local communication between processors in a rigorous manner. However, more research is required to establish the properties of metrics defined by coordinate bases; in particular, it is not yet clear how the choice of the coordinate basis affects the metric.

3.3 SCHEDULES, DELAY AND THROUGHPUT

The execution of an MCN represents only its precedence relation and does not take into account the actual time required for execution. The evaluation of each variable requires a certain amount of execution time when implemented in hardware. Since each output of a processor may involve a different execution delay, execution times have to be specified for arcs of the precedence graph rather than for the vertices. The execution time associated with a variable x will be denoted in the sequel by $T(x)$. This is the time required to evaluate x from its immediate ancestors (= parents), i.e., from the variables that serve as inputs to the processor whose output is the variable x .

The incorporation of time delays into the notion of execution results in a schedule, which is formally defined as a function $\tau(x)$ that satisfies the constraint

$$\tau(x) \geq T(x) + \max_y \{ \tau(y) ; y \in a(x) \} \quad (3.8a)$$

and is zero for the network inputs, viz.,

$$x \in X_1(P) \Rightarrow \tau(x) = 0 \quad (3.8b)$$

This constraint guarantees, in particular, that the parents of x will be available at time $\tau(x)$. Thus, schedules are refinements of executions. In particular, with every execution $E(\)$ we can associate a schedule $\tau(\)$ by choosing

$$\tau(x) = \max_y \{ \tau(y) + T(x) ; E(y) = E(x) - 1 \} \quad (3.9)$$

Such schedules are, generally, non-minimal in the sense that some operations have all their inputs available before their scheduled execution time, i.e., (3.8) holds with a strict inequality for such operations. A schedule which satisfies (3.8) with equality for every $x \in X$ is called minimal.

Minimal schedules are important because they characterize the fastest executions of a given MCN. This property is made explicit by the following result.

Theorem 3.2

Every structurally finite MCN has a unique minimal schedule $\hat{\tau}()$. The minimal schedule satisfies

$$\hat{\tau}(x) \leq \tau(x) \quad (3.10)$$

for every $x \in X$ and for every schedule $\tau()$.

Proof:

Since by Theorem 2.1 a structurally finite MCN has a countable number of variables, the result can be established by induction. Thus, let S be a subset of X that is closed under the ancestry relation, namely for every $x \in S$ we must have $\alpha(x) \subset S$. Assume that S has already been assigned a minimal schedule $\hat{\tau}()$ and that this schedule also satisfies (3.10).

Choose a variable y not in S and consider the augmented network determined by $S \cup \alpha(y)$. We need to show that $\hat{\tau}()$ can be extended to this augmented network and that it will satisfy both (3.8) and (3.10). The schedule $\hat{\tau}()$ is now extended to $\alpha(y)$ in the following manner:

- (i) Assign $\hat{\tau}(z) = 0$ to every $z \in \alpha(y)$ that has no ancestors.
- (ii) Identify the collection of variables for which all ancestors have already been assigned a schedule (this set is never empty). Assign to each one of these variables the schedule

$$\hat{\tau}(z) := T(z) + \max_w \{ \hat{\tau}(w) : w \in \alpha(z) \}$$

For every $w \in \alpha(z)$, either $\tau(w) = 0$ or $w \in S$, so that $\hat{\tau}(w) \leq \tau(w)$ for any schedule $\tau(\cdot)$. Since any schedule $\tau(\cdot)$ has to satisfy (3.8) we obtain

$$\begin{aligned}\tau(z) &\geq T(z) + \max_w \{\tau(w); w \in \alpha(z)\} \\ &\geq T(z) + \max_w \{\hat{\tau}(w); w \in \alpha(z)\} = \hat{\tau}(z)\end{aligned}$$

which proves that (3.10) is preserved in this step.

(iii) Augment S , viz.,

$$S := S \cup \alpha(y)$$

and go back to (ii).

The repeated application of this procedure results in the assignment of $\hat{\tau}(x)$ to every variable of the MCN. The resulting schedule is minimal, i.e., it satisfies (3.8) with an equality, unique (by construction) and also satisfies (3.10).

As with executions, we can also define schedules for processors. The schedule of a processor $p \in P$ is defined as

$$\tau(p) := \max_x \{ \tau(x); x \in X_i(p) \} \quad (3.11)$$

in analogy with 3.3. It is the instant at which all input variables of the processor become available. Some of the inputs of the processor may become available earlier and need, therefore, storage or buffering until they can actually be used. A variable x is called critical with respect to a given schedule $\tau(\cdot)$ if

$$x \in X_i(p) \Rightarrow \tau(x) = \tau(p) \quad (3.12)$$

and non-critical otherwise. Thus, the schedule of each processor is determined by the schedule of its critical inputs. Since non-critical variables require storage the general objective of scheduling is to reduce the total storage requirements.

Storage is measured by the product of volume (e.g., the number of bits to be stored) and duration. The duration of storage for a variable $x \in X_1(p)$ is the difference between the time it becomes available and the most recent instant it still needs to be available, i.e.,

$$\max \{ \tau(y) - T(y); y \in X_0(p), x \rightarrow y \} - \tau(x)$$

This interval will be minimized if we choose the difference $\tau(y) - T(y)$ as short as possible. In view of (3.8), we have to choose $\tau(y) - T(y) = \tau(p)$, namely the minimal schedule also minimizes the storage requirements of the network. The minimal schedule still has both critical and non-critical variables. However, only the critical ones determine the schedule, as demonstrated by the following result.

Lemma 3.3

Every processor in a structurally finite MCN is connected to a network input by a finite path whose variables (arcs) are critical under the minimal schedule.

Proof:

The definition of a critical variable implies that every processor has at least one critical input variable. The critical path is obtained by tracing back through the critical inputs of the preceding processors. Since the ancestry of each processor is finite, this procedure terminates in a finite number of steps when the path reaches a network input.

Corollary 3.3

The minimal schedule of a processor equals the length (sum of processing delays) of a critical path that connects a network input to this processor.

The corollary implies an interesting principle for the physical design of hardware implementations--critical paths need to be considered first so that the length of the physical connections along the path can be minimized. Non-critical paths can accommodate extra propagation delays and can, therefore, be designed later.

The construction of a schedule is based upon the assumption (3.5b) that all MCN inputs are available at the very beginning. Thus, a zero schedule was assumed in (3.8) for every MCN input, i.e.,

$$x \in X_i(P) \Rightarrow \tau(x) = 0$$

This is, however, inessential, since many of these inputs will not be required until much later. The scheduling of the network inputs can be modified, once a schedule $\tau(\)$ has been determined, to reflect the earliest instant they are required in the execution. Thus, for every $x \in X_i(P)$ redefine the schedule of the inputs to be

$$x \in X_i(P) \Rightarrow \tau(x) := \tau(p) \quad \text{where } x \in X_i(p) \quad (3.13)$$

and no buffering, or storage, of the inputs will be necessary. This is particularly important if not all the inputs can be made available in the same instant, e.g., in real time processing of time-series. Notice that this modification in the scheduling of inputs does not affect the schedule of any other variable in the network. This is so because only non-critical input variables are adjusted. The meaning of (3.13) is that all network inputs are made critical to reduce the storage requirements of the network.

The schedule of output variables is commonly known as delay. The delay of x is the time that has elapsed from the moment some variable in $a(x)$

becomes available until the moment the variable x itself becomes available. This is, clearly,

$$\tau(x) = \min \{ \tau(y); y \in a(x) \}$$

and in many cases it will be equal to $\tau(x)$. In typical signal processing applications the delay of outputs usually increases without limit as more and more inputs are applied to the processor and more and more outputs are evaluated. In such cases one is interested in the rate of output evaluation, commonly known as throughput, rather than in the delay of the outputs. The throughput is roughly the number of MCN outputs that are evaluated in a unit of time. Since this rate may vary, we need a more rigorous definition based on the concept of schedule.

Every schedule determines a temporal ordering of the MCN variables (it need not be sequential), which is consistent with the precedence relation between variables. In order to quantify the rate at which output variables are evaluated, we define the output counting function

$$N_o(\tau) := \text{number of elements in the set} \quad (3.14)$$

$$\{y; y \in X_o(P), \tau(y) < \tau\}$$

The input counting function can be similarly defined, viz.,

$$N_i(\tau) := \text{number of elements in the set} \quad (3.15)$$

$$\{y, y \in X_i(P), \tau(y) < \tau\}$$

We can now plot the counting function $N(\tau)$ as a function of τ for both the inputs and the outputs (Figure 3-2). The functions $N_i(\tau); N_o(\tau)$ are, of course, staircase functions (indicated by broken lines in Figure 3-2) and can be upper-bounded by a pair of continuous, piecewise-linear curves (indicated by the solid lines in Figure 3-2). The slope of these

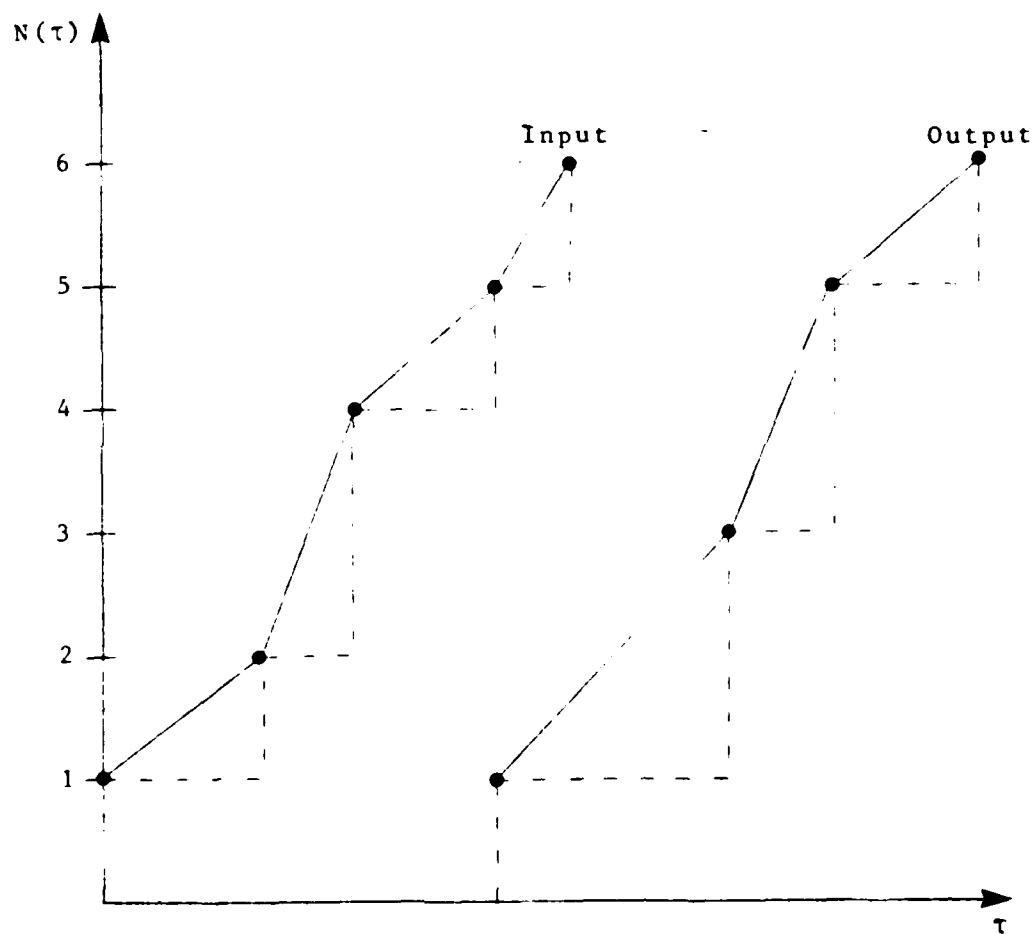


Figure 3-2. Input and Output Throughputs of an MCN.

curves (which are always strictly monotone increasing) is a measure of the rate of information flow into the network and out of it, and will be called the input and output throughput, respectively. A schedule is called regular when both its input and output throughput are periodic with the same period (and, in particular when both throughputs are constant). An MCN is called temporally-regular when its minimal schedule is regular. Many temporally-regular networks have equal input and output throughputs, but this need not be true, in general.

3.4 SPACE-TIME DIAGRAM

The continuous-time character of the schedule is best demonstrated by introducing a time-axis into the graphical description of an MCN. The vertices are arranged so that the vertical displacement from the top of the diagram to the location of any given vertex p indicates, on an appropriate scale, the value of the schedule $\tau(p)$ for this vertex (Figure 3-3, compare with Figure 2-1). This space-time diagram has several interesting properties:

- (1) All arcs point downward.
- (2) The vertical displacement of an arc indicates the total execution time associated with this operation, including any buffering time that may be required beyond the actual execution time $T(x)$.
- (3) Changes in local execution times are easily accounted for by shifting the corresponding vertices up or down along the time scale. The global effects of such shifts are clearly depicted by the diagram.
- (4) Non-executable MCNs (with zero or negative execution times) can still be described by the diagram. This is useful to establish equivalence between various descriptions of the same MCN (e.g., precedence graphs and signal flow graphs).

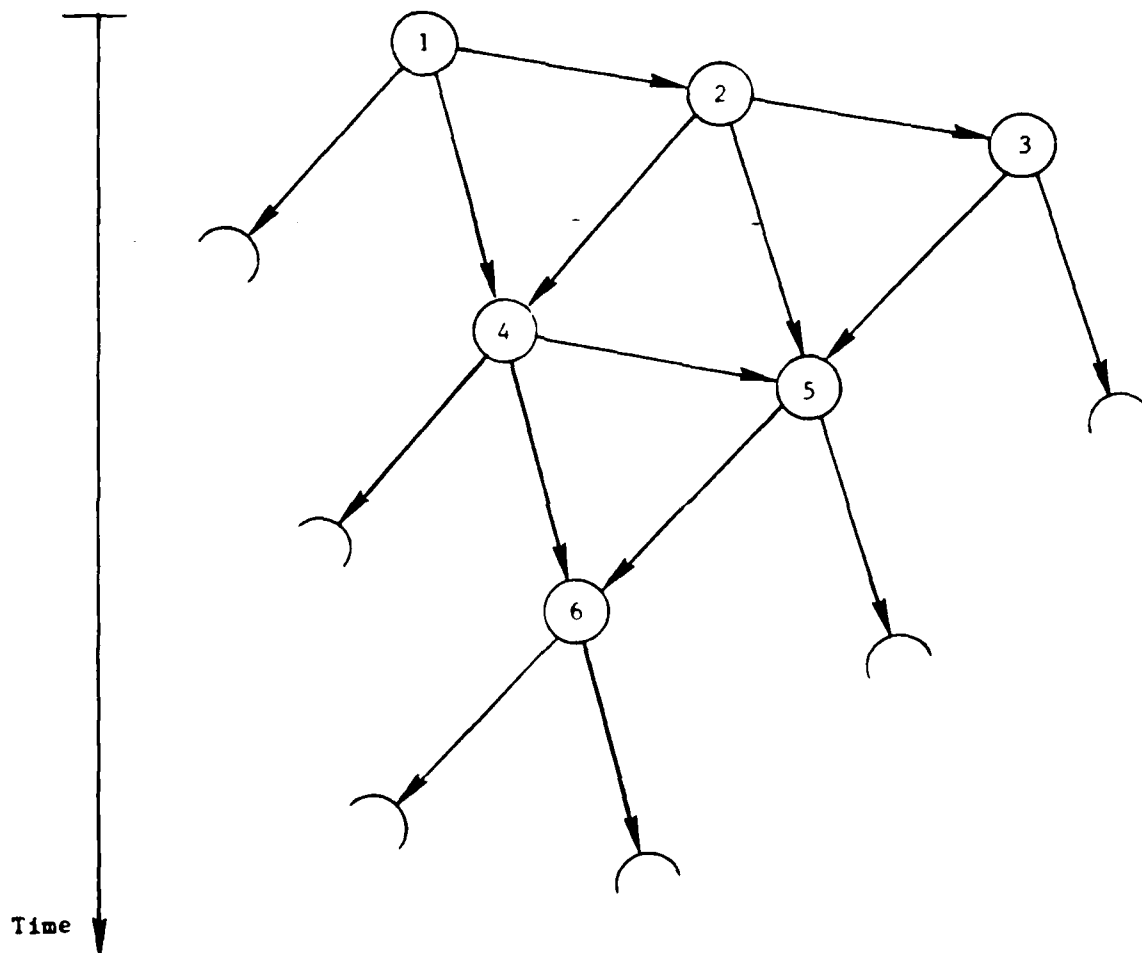


Figure 3-3. Introduction of a Time Scale into the Architecture

The collection of processors (vertices) with the same schedule form an isochrone.

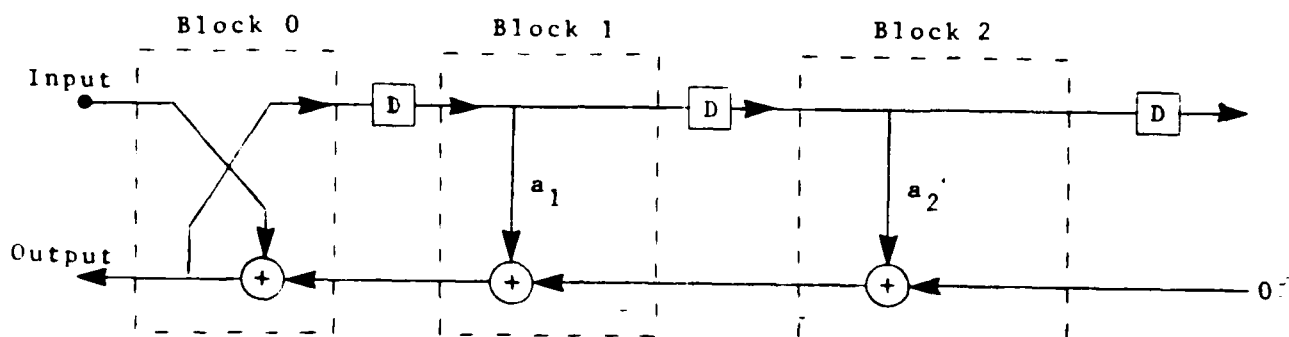
The execution of a network according to a given schedule may now be interpreted as the propagation of a single wavefront of activity through the architecture. The location of the activity wavefront at any given instant is indicated by the corresponding isochrone. Observe that the isochrones are parallel straight lines (or parallel planes if the precedence graph is described in a three dimensional space) and do not intersect. Also notice that the inputs and outputs of a temporally-regular network are evenly distributed in time (i.e., along the vertical axis of the space-time diagram). These properties are particularly significant for the analysis of iterative MCNs, which is carried out in Section 4.

As an illustration of the equivalence between various descriptions of the same MCN consider the block-diagram of an IIR filter (Figure 3-4a). The corresponding MCN (Figure 3-4b) can be rearranged in many ways without modifying the architecture of the network. However, if Figure 3-4b is interpreted as a space-time diagram (with time being the vertical axis), such modifications result in different schedules and also in different block-diagrams. In particular, the delay elements can be moved to the lower path (Figure 3-5) or split between the two signal paths (Figure 3-6). The latter version is the only one that can be implemented in hardware because it contains only downward-pointing arrows; the other two versions require instantaneous evaluation of each variable associated with a horizontal arrow. The third description makes it also clear that the time interval between successive application of inputs is equal to two delay units. It is also possible to associate unequal computing times with the forward and backward propagation through each block. After all, the forward path only feeds information through the block while the backward path involves a multiply-and-add operation. The resulting space-time diagram (Figure 3-7) has delays T_f , T_b associated with the forward and backward paths, and the input interval is clearly $T_f + T_b$. Notice that the block diagram description involves two different delay blocks: This is known as a multirate implementation [8]. The throughput rates are, nevertheless, equal to $(T_f + T_b)^{-1}$ for both the input and the output.

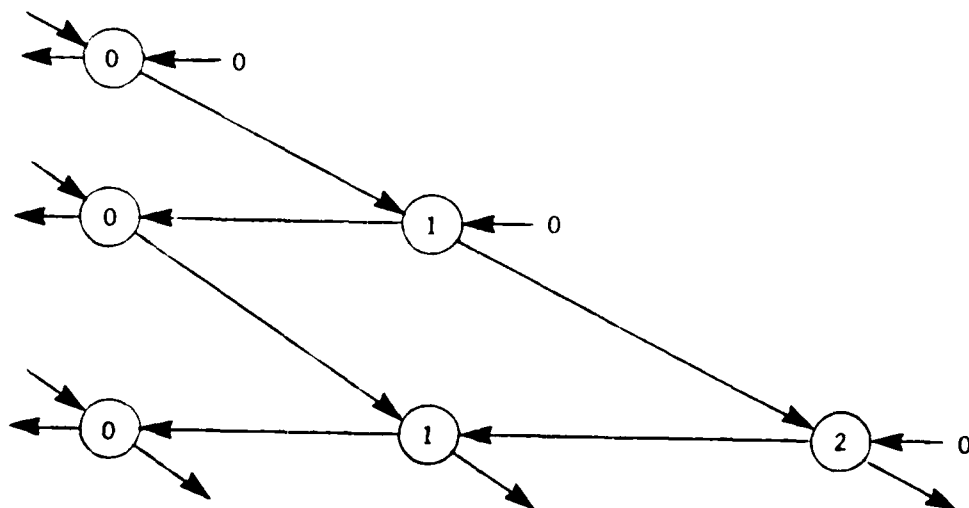
The same technique can be applied to analyze the several proposed systolic-array-like implementations for matrix multiplication: the

hexagonal array of H.T. Kung [5], the improved hexagonal array of Weiser and Davis [4], the wavefront array processor of S.Y. Kung [7] and the direct form realization of S. Rao [10]. Details are provided in Appendix E.

The analysis of the previous examples makes it clear that the common MCN architecture shared by all the representations of a given processing system induces certain invariants. For instance, the total number of outputs of each processor remains invariant, even though in some representations some of these outputs are connected to a local memory rather than to a nearby processor (Figure 3-8). The same is true for the total number of inputs of each processor. Notice that the blocks in Figure 3-8a are still the same as in Figure 3-4a, including the orientation of paths (one forward, one backward). On the other hand, the roles of the blocks are quite different; in particular, outputs are obtained from the local memories rather than from the left-most block alone, as in Figure 3-4a.

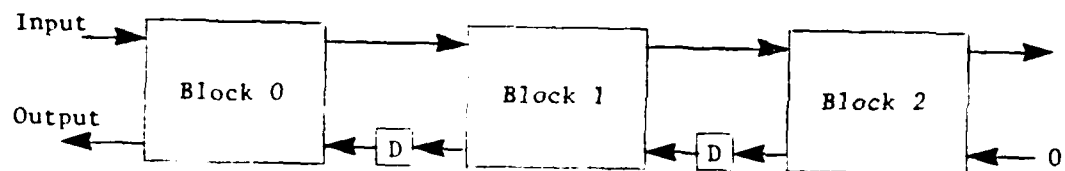


a. Block-diagram

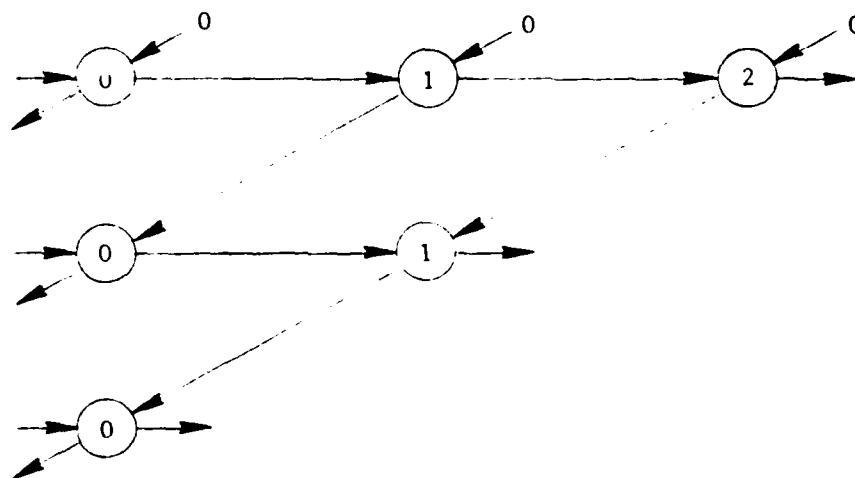


b. Space-time diagram

Figure 3-4. Schematic Description #1 of an IIR Filter

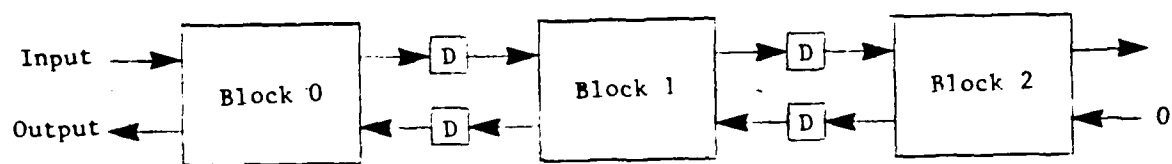


a. Block-diagram

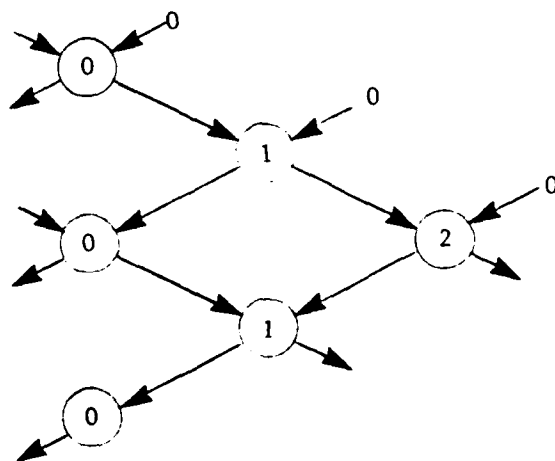


b. Space-time diagram

Figure 3-5. Schematic Description #2 of IIR Filter

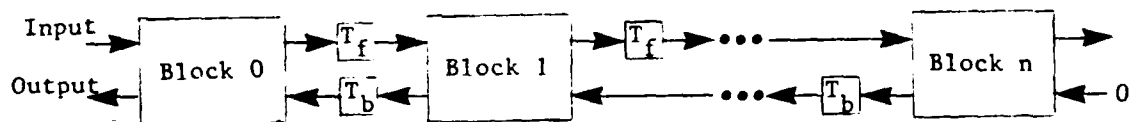


a. Block-diagram

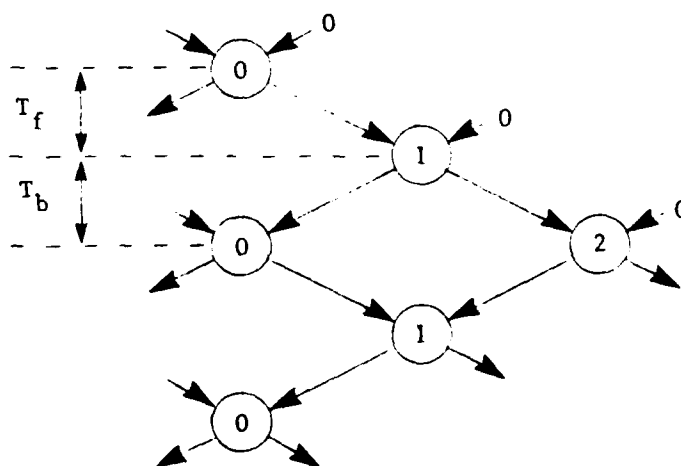


b. Space-time diagram

Figure 3-6. Schematic Description #3 of an IIR Filter

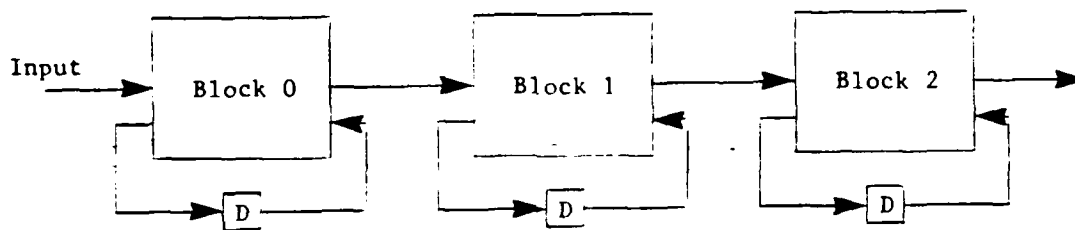


a. Block diagram

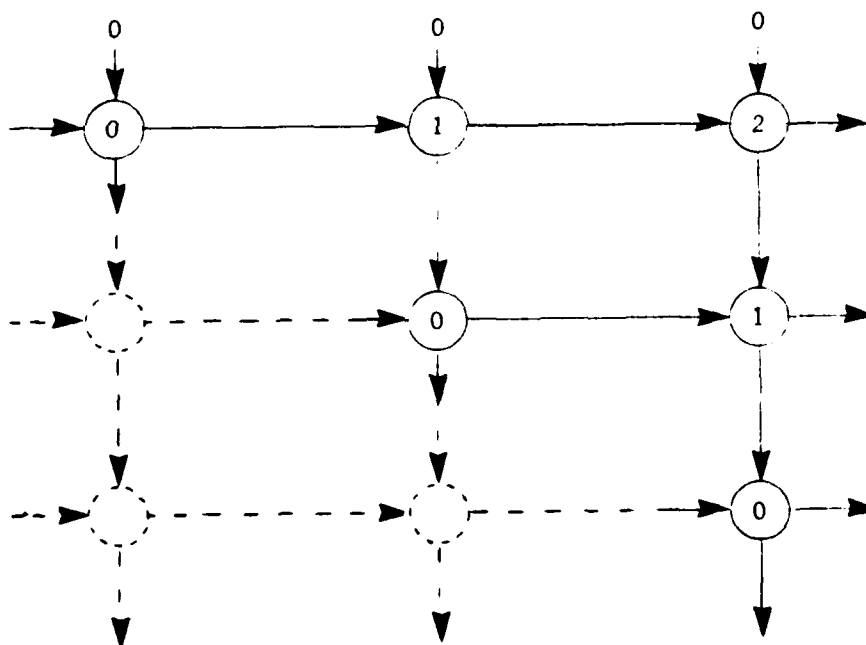


b. Space-time diagram

Figure 3-7. Multirate Implementation of an IIR Filter ($T_f < T_b$)



a. Block diagram



b. Space-time diagram

Figure 3-8. Schematic Representation of IIR Filter Involving Local Memory

SECTION 4

ITERATIVE NETWORKS

An MCN is called iterative when it can be described as a sequential composition of identical subnetworks, i.e.,

$$\mathcal{G}_{\text{network}} = \mathcal{G} * \mathcal{G} * \dots * \mathcal{G}$$

Each of the identical components \mathcal{G} will be called an iteration. One reason for this name is that the MCN can be executed by implementing a single component \mathcal{G} in hardware and simulating a sequential composition of such components by spreading the execution of the components in time. The motivation for studying iterative MCNs is that most signal-processing algorithms and, in particular, all systolic-array-like architectures can be described by such networks. Observe that every block-diagram representation corresponds to an iterative MCN. The iterative structure induces certain regularity constraints upon the MCN which lead to a simplified representation.

4.1 PROPERTIES OF ITERATIVE MCNs

The minimal schedules of iterative networks are, clearly, periodic with the same period for input and output schedules. Thus iterative MCNs are temporally-regular. In addition, they are functionally-regular in the sense that each iteration involves the same function \mathcal{F} . Consequently, their properties can be determined by analyzing a single iteration. For instance, the entire network is acyclic (hence executable) if a single iteration is acyclic. In particular, the executability of z-transform representations of iterative MCNs is tested by removing all separators and examining the remaining directed graph for occurrence of cycles (see also [9]).

Similarly, the (minimal) schedule of the network can be determined by considering a single iteration.

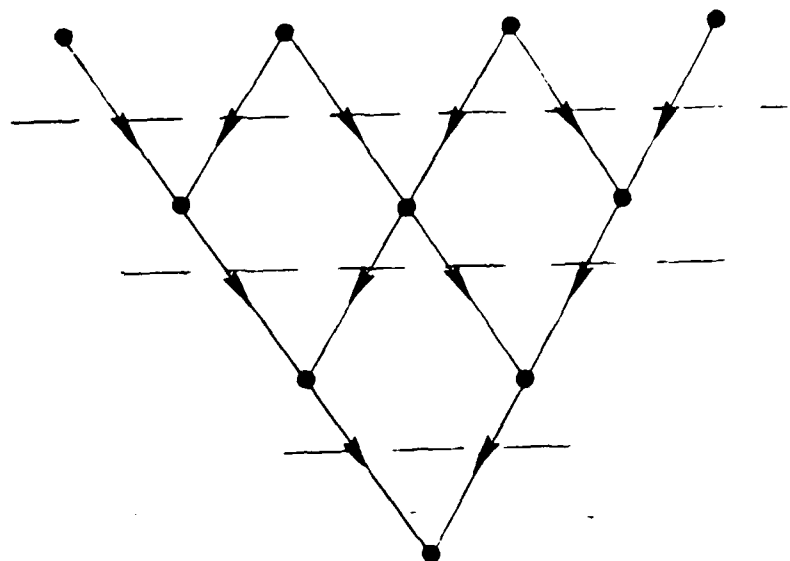
Iterative MCNs are commonly described by recursion equations (or equivalently by z-transform diagrams), data-flow diagrams (marked graphs), or by 'do-loops' in high-level programming languages. While precedence graphs of iterative networks still indicate all possible executions, recursion equations restrict the choice of execution to one or at most two possibilities (Figure 4-1). And while precedence graphs avoid the pitfall of non-executable iteration by explicitly describing each iteration as part of an executable (acyclic) precedence graph, data-flow diagrams contain cycles which may cause the entire MCN to be non-executable.

Since all iterations are identical, the schedules of every two consecutive iterations differ by the same constant, which we shall call the input interval. The input interval is the period of the input schedule or, equivalently, of the input throughput, as well as of the output schedule (recall that iterative MCNs are temporally regular). It determines an upper bound on the rate at which inputs are applied to the network (lower rates are permitted, but require additional buffering).

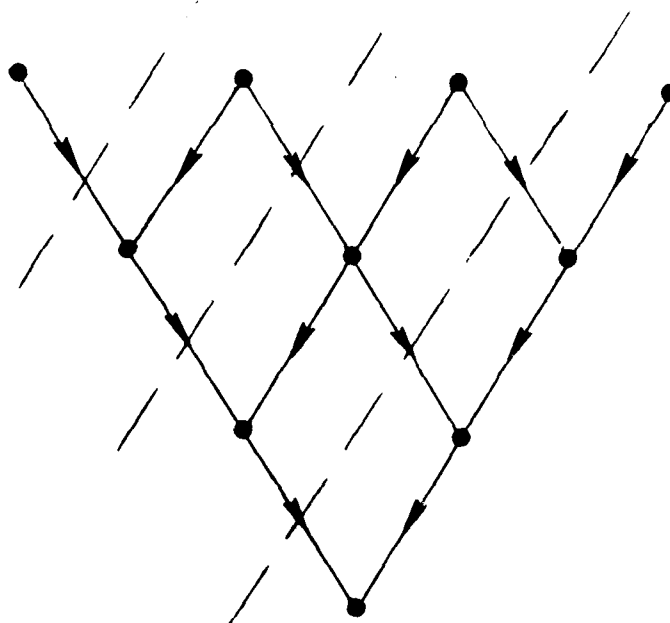
The time-space diagram of an iterative MCN corresponds to its minimal schedule and is, therefore, periodic. It is important to notice that the period (= input interval) is, in general, shorter than the time required to complete the execution of a single iteration (= the iteration delay). This means that hardware realizations of the MCN can be pipelined: New inputs can be applied before the processing of previous inputs has been completed. The following section provides a detailed analysis of pipelinability in MCNs.

4.2 HARDWARE ARCHITECTURES

The functional regularity of iterative MCNs implies that they can be implemented in special purpose VLSI hardware by mapping the precedence graph of a single iteration directly into silicon. Each processor is mapped into a cell ('processing element') and precedence relations are mapped into interconnections between cells. Neither translation nor hardware compilation are required to accomplish this mapping since the hardware



a. Parallel Input Application



b. Sequential Input Application

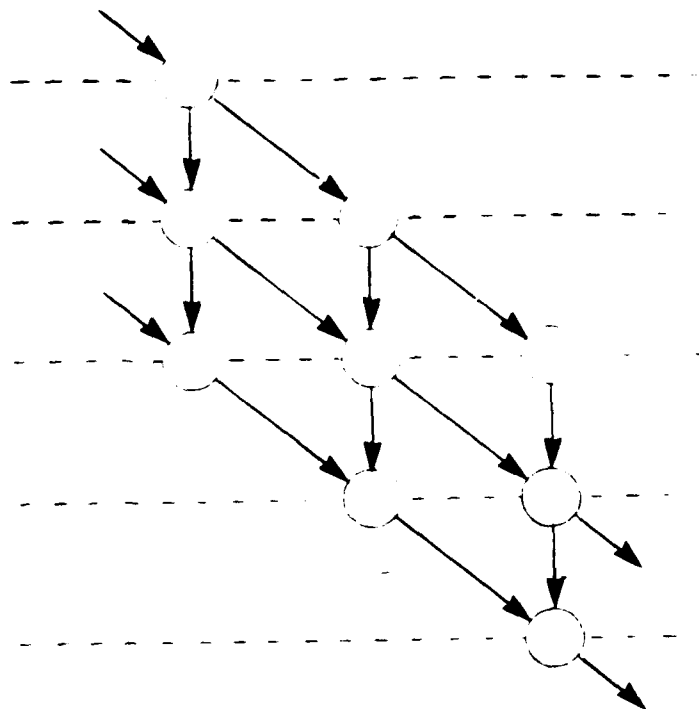
Figure 4-1. Equivalent Pipelined Executions of an MCN.

architecture is an exact image of a single layer of the network architecture. An execution is now interpreted as the propagation of a sequence of wavefronts through the hardware rather than the propagation of a single activity wavefront through the iterative MCN (Figure 4-2). The time spacing of these wavefronts equals the period of the underlying MCN minimal schedule.

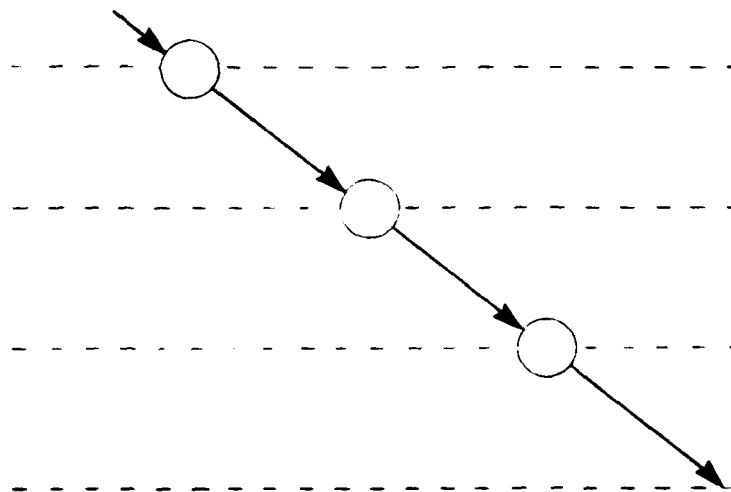
Since a single layer of the MCN is used to 'simulate' the entire network each processor is activated many times and each arc of the hardware architecture corresponds to a time-series of variables rather than to a single variable. This raises a design problem of a new kind: It is necessary to guarantee that variables do not disappear before they have been used to evaluate their successors. There are three different solutions to this problem:

- (1) Iterative execution: A new iteration is initiated only after the execution of the preceding iteration has been completed. This means that the input interval is extended (by buffering of intermediate results) to the length of the iteration delay, and the time-overlap between iterations is completely eliminated.
- (2) Scheduled execution: The (minimal) schedule of the network is determined in advance and execution is carried out according to schedule. Buffering is provided to guarantee the availability of inputs to processors on schedule (only non-critical variables need to be buffered).
- (3) Self-timed execution: Processors are activated as soon as their inputs become available. Acknowledgment signals ('hand-shaking') are used to guarantee the correct transfer of data between processors.

While scheduled execution offers the shortest execution time and requires a fairly simple control system, it is extremely sensitive to scheduling perturbations. Such perturbations, which are caused by clock-skewing and local variations in execution times, may result in loss of synchronization between cells and a complete failure of the system. Iterative execution is insensitive to scheduling perturbations and requires a very simple control system, but wastes processing time since the hardware is idle most of the time. Self-timed execution provides a nice tradeoff between these two extremes: Its execution time is only slightly longer than the theoretical minimum achieved by scheduled execution; and the control system it requires



a. MCN Perspective



b. Hardware Architecture Perspective

Figure 4-2. Execution Interpreted as Activity Wavefront Propagation

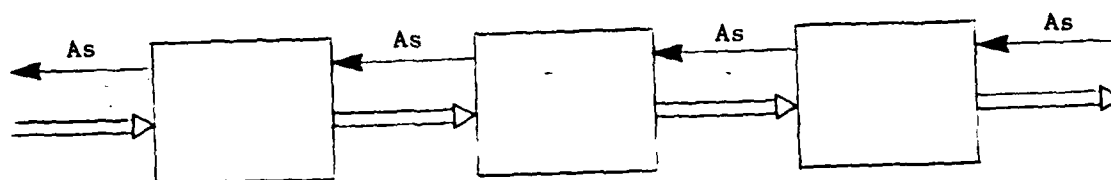
has about the same complexity as the timing system for scheduled execution. It is interesting to observe that the conditions for self-timed execution [11], [12] coincide with the concept of admissible composition, which was shown to be the necessary and sufficient condition for executability in general. Thus, every MCN can be implemented as a self-timed system.

The notion of self-timed execution suggests the introduction of self-timed block-diagrams. These are obtained by removing the delay-elements from a conventional block-diagram and replacing them by direct connections. The hardware implementation of such self-timed diagrams is straightforward provided two simple rules are obeyed:

- (i) Each cell is activated as soon as all its inputs become available and deactivated as soon as all its outputs have been evaluated.
- (ii) Each input variable is accompanied by an acknowledgment line. Each input port (sink) acknowledges the arrival of a new input variable to the processor that evaluated this variable. The acknowledgment is sent when the processor connected to the input port becomes activated.

These rules assume that each cell is provided with sufficient memory to store its output variables until they become acknowledged.

The acknowledgment of inputs associated with self-timed implementations can (and should) be reflected in the space-time diagram of the network. Acknowledgment signals are just one more set of variables in the network, and are represented in the space-time diagrams by arcs, as any other variable. For instance, a cascade connection of (identical) processors (Figure 4-3a) has an input interval of $\tau_1 + \tau_2$ where τ_1 is the execution time of the processor and τ_2 is the delay between the reception of an acknowledgment signal from the subsequent processor and the transmission of an acknowledgment signal to the preceding processor (Figure 4-3b). The interval τ_2 includes the propagation time through the processor and the connecting wires plus the time required to carry out checks on the input data (parity, error detection, fault detection, etc.). Notice that the need for explicit acknowledgment can be eliminated in many cases, e.g., when there is an information carrying path along the cascade in the backward direction.



a. Self-Timed Block-Diagram

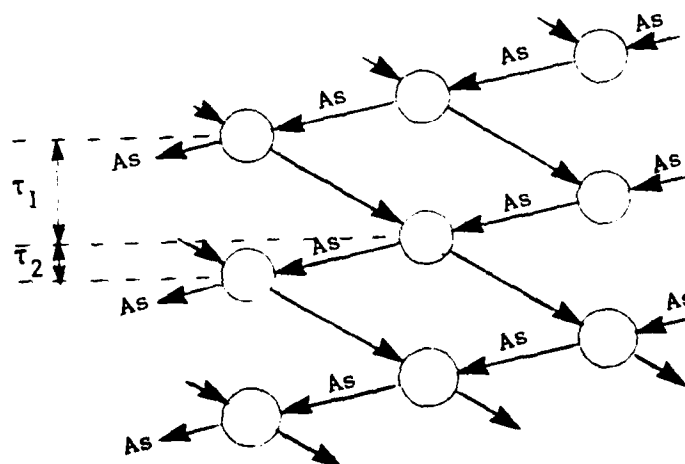
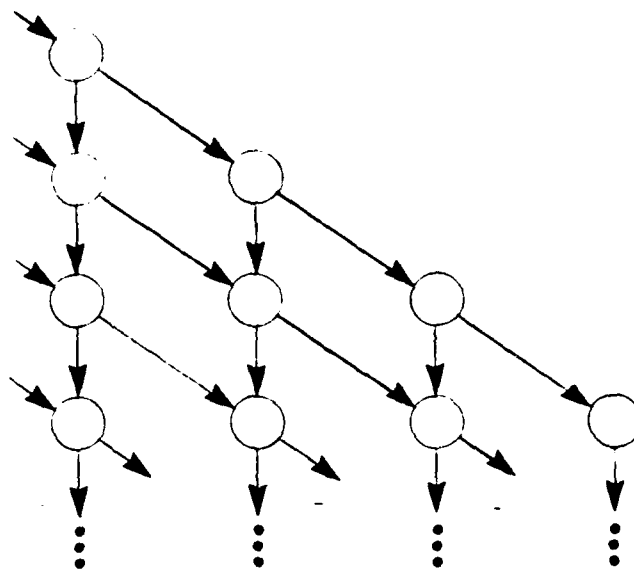


Figure 4-3. Propagation of Acknowledgment Signals (AS) in Self-Timed Systems

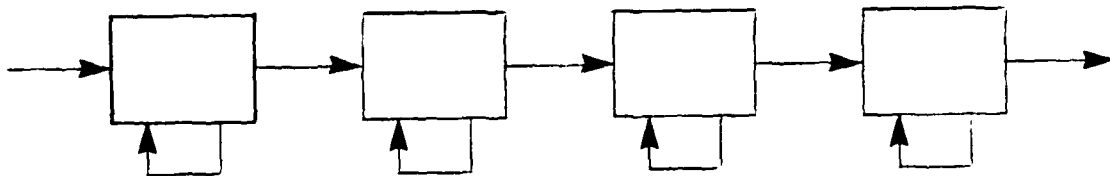
The horizontal dimension of space-time diagrams can now be interpreted as hardware: Processors located along the same horizontal line (isochrone) represent computations that need to be carried out simultaneously and must, therefore, be implemented in parallel hardware. We shall adopt the convention of interpreting the vertical dimension of space-time diagrams as pure time: Processors located along the same vertical line will represent computations that are carried out by the same processing element but during different (non-overlapping) intervals of time. Thus, for instance, the MCN of Figure 4-4 can be implemented in hardware with four processing elements (Figure 4-4b). Each vertical column of processors in the space-time diagram of the MCN (Figure 4-4a) is mapped into a single hardware cell; connections between columns are mapped into physical connections between cells and connections within columns are implemented by locally storing intermediate results inside the appropriate cells. However, the correspondence between space-time diagrams and hardware block diagrams is not always so straightforward. For instance, the various representations of the IIR filter (Figures 3-4 through 3-6) seem to indicate that the hardware implementation of an m -th order filter requires $m + 1$ processing elements. However, we also observe that only 50% of these elements are active at any given instant of time. Thus, it is possible to cut the number of processing elements by half without affecting the schedule at all (Figure 4-5a). In general, every two processors p, q whose schedules satisfy

$$\tau(q) \geq \max \{ \tau(x); x \in X_0(p) \} \quad (4.1)$$

can be implemented as a single hardware cell, which first evaluates the outputs of p , then the outputs of q . The condition (4.1) guarantees that the computations represented by the processor p are completed before the computations represented by the processor q are started. Since adjacency of processors in the time-space diagram is, in general, mapped into spatial adjacency of hardware cells, the merging of non-adjacent processors into a single hardware cell will require a complex network of interconnections between cells. In order to reduce the complexity of cell interconnections to a minimum only adjacent cells can be considered as candidates for merger. The most frequent example of such merger is the interleaving of two adjacent columns, as in Figure 4-5.

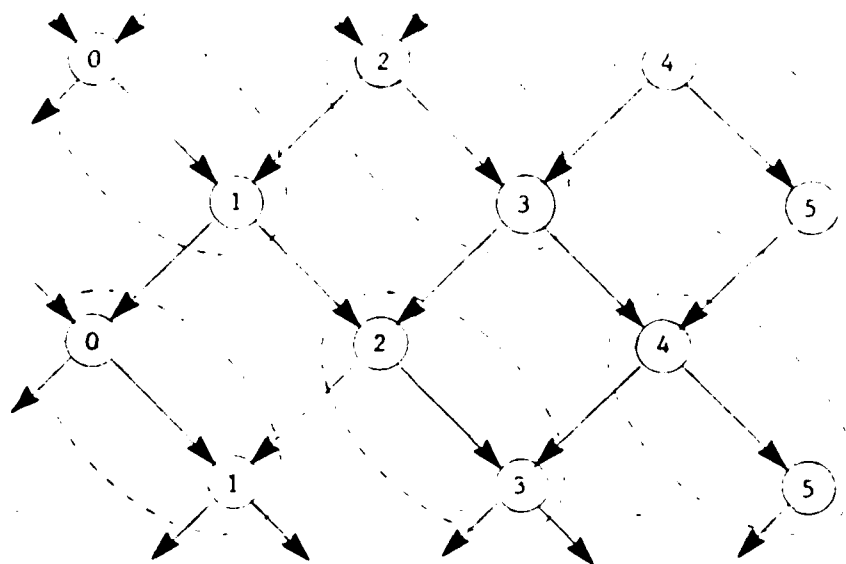


a. Space-Time Diagram

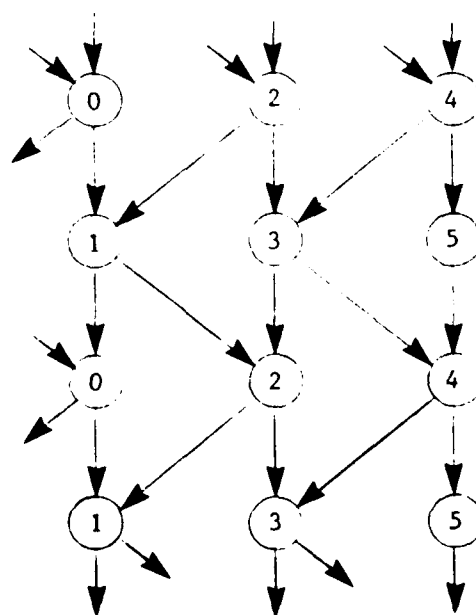


b. Self-Timed Block-Diagram

Figure 4-4. Hardware Implementation of an Iterative MCN.



a. Direct Form



b. Interleaved Form

Figure 4-5. Resource Sharing by Interleaving

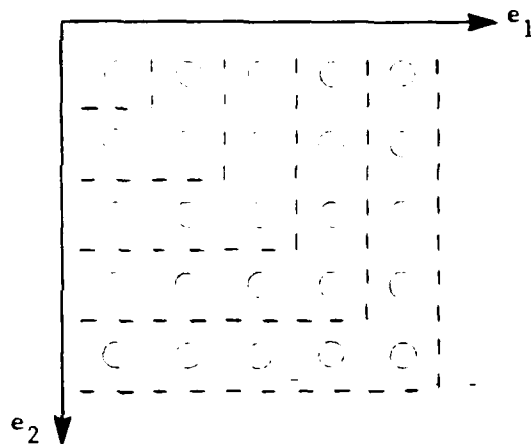
Self-timed or scheduled execution is, indeed, faster than iterative execution only if the input interval is shorter than the execution time of a single iteration. An implementation of such an execution will initiate a new iteration before the execution of the previous iteration has been completed. Such implementations deserve to be called pipelined. Thus, iterative executions are never pipelined, while self-timed (or scheduled) executions are pipelined only for pipelinable MCNs.

Notice that the input interval is uniquely defined for every temporally-regular MCN, but the iteration delay (= execution time of a single iteration) depends upon the partitioning of the MCN into iterations. Since this partitioning need not be unique, an iterative MCN may have several hardware realizations, each with a different iteration delay. Thus, pipelining is primarily a property of a given hardware realization. An MCN is considered pipelinable if it has at least one pipelined realization. Pipelinability is most frequently associated with completely regular MCNs (= systolic-array-like networks). The connection between complete regularity and pipelinability is discussed in the following section.

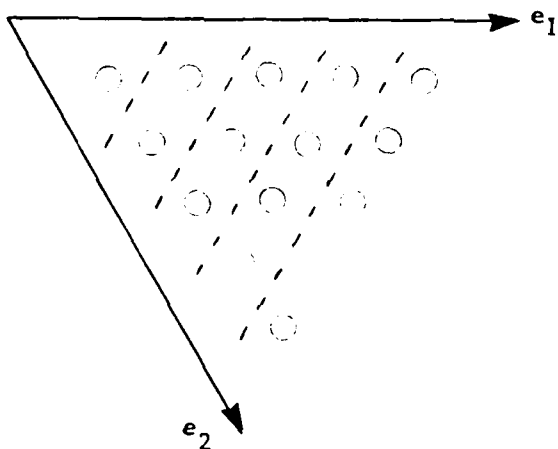
4.3 COMPLETELY REGULAR MCNs

An iterative MCN is called completely regular if it satisfies the four following conditions:

- (i) All processors are identical, i.e., have the same input-output map.
- (ii) The architecture of a single iteration is regular, i.e., it can be represented by a regular multidimensional grid (also known as mosaic in the 2-D case [21]).
- (iii) The architecture of a single iteration is nested, i.e., it can be considered as a sequence of architectures of growing size, each being obtained from the previous one by adding cells in a regular manner (Figure 4-6).
- (iv) The minimal schedule of the network is regular. This means that adding the time dimension to the regular representation of a single iteration produces a regular space-time diagram.



a. Square



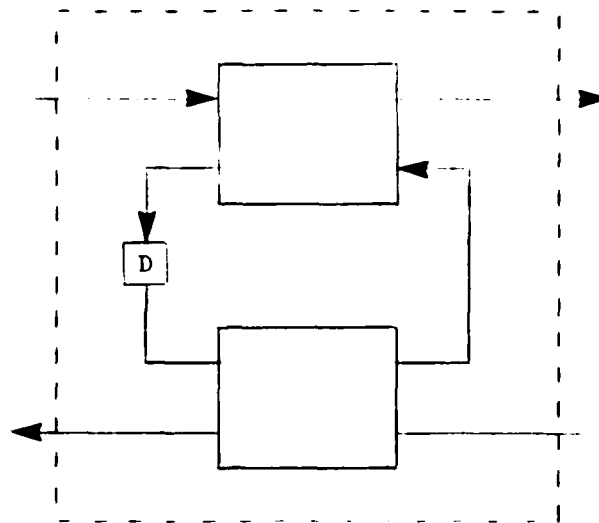
b. Triangular

Figure 4-6. Examples of Nested Iteration Architectures and Their Natural Coordinate Bases

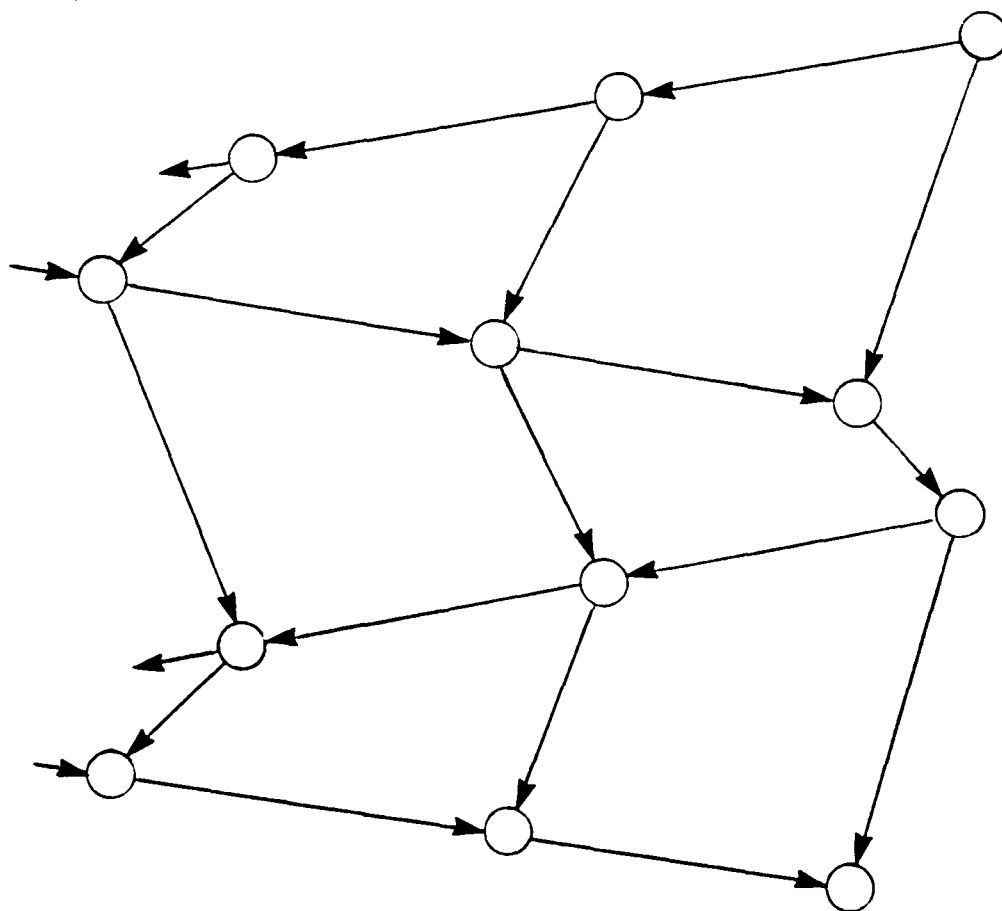
The last condition is important, for it is quite possible to have regular architectures with identical processors yet irregular schedules (Figure 4-7). A network of the form described in Figure 4-7 is, clearly, not pipelinable: The input interval coincides with the iteration delay. A completely regular network, on the other hand, has an input interval that is much shorter than the iteration delay, and is, therefore, pipelinable.

The nestedness of a completely regular architecture is a purely spatial attribute. The temporal dimension of the corresponding space-time diagram is not affected when the size of the nested architecture varies. In particular, the input interval is fixed and does not depend upon the spatial extent of the space-time diagram. The iteration delay, on the other hand, increases as the spatial extent of the network increases, since each iteration involves more and more processors. Consequently, the input interval is less than the iteration delay, i.e., the MCN is pipelinable. The invariance of the input interval with order (= spatial extent of the network) is sometimes taken as the definition of pipelinability [9]. However, this invariance is guaranteed only for completely regular MCNs: It is possible to have pipelinable iterative networks whose input interval grows (slowly) with order.

A completely regular MCN determines a coordinate basis for a single iteration in a natural manner. Adding the temporal dimension to this spatial basis produces a set of coordinates for the complete MCN (i.e., for its space-time diagram). It is interesting at this point to relate this basis to the more abstract definition provided in Section 3.2 for arbitrary MCNs. That definition was based upon the notion of representative families of sequential executions, which are highly nonunique. The natural coordinate basis associated with a completely regular architecture also provides a natural and unique choice of a representative family. This is accomplished by considering the lexicographic ordering of processors induced by the basis. The coordinates (e_1, \dots, e_n) , which for a completely regular MCN have integral values, are scanned from e_1 to e_n . This means that the lexicographic ordering of vertices of a 2-D square grid of size 3 is: 11, 21, 31, 12, 22, 32, 13, 23, 33. Each cyclic permutation of (e_1, \dots, e_n) determines one sequential execution, and the totality of n sequential executions form a representative family. The corresponding coordinate basis is consistent with the natural basis (e_1, \dots, e_n) .



a. Block Diagram



b. Space-Time Diagram

Figure 4-7. Example of a Regular Architecture That is Not Pipelinable

SECTION 5

CONCLUSIONS

A modeling and analysis methodology for parallel algorithms and architectures has been presented. Modular computing networks (MCNs) were introduced as a unifying concept that can be used to describe both algorithms and architectures. The representation of an MCN exhibits all the relevant information that characterizes a parallel processing algorithm, from precedence relations and order of execution, through scheduling and pipelinability consideration, to map compositions and global characterization. It clearly displays the hierarchical structure of a parallel system and the multiplicity of choices for hardware implementation. Our methodology applies both to arbitrary (irregular) networks and to iterative ones. Regularity of networks translates directly into regularity of the model we use to describe them and, consequently, into regularity of the associated architectures. Problems of non-executability (deadlocks, safeness, etc.) are insignificant in our methodology and can be easily detected and resolved.

Infinite MCNs, which occur in most signal processing applications, have been characterized. It has been shown that the key property for executability of such networks is structural finiteness (in addition to absence of cycles, of course). Infinite MCNs are most frequently iterative, in which case they are guaranteed to be structurally finite and can be represented by a finite single-layer diagram.

There exist three distinct modes of execution for iterative networks: iterative, scheduled and self-timed. Iterative execution is simple but slow and storage-intensive. Scheduled execution is fast but sensitive to schedule perturbation caused by clock skewing. Self-timed execution offers a simple and robust alternative at the cost of introducing handshake protocols between communicating processors. It is the best choice for large networks containing many processors.

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APPENDIX A
PROOF OF THEOREM 2.2 FOR INFINITE MCNs

If the MCN has an execution then it must be acyclic, as was pointed out at the beginning of Section 2.3. To prove the converse we shall construct an execution for an arbitrary acyclic, structurally-finite MCN.

First, notice that, by Theorem 2.1, the inputs of the MCN can be numbered. Let us, therefore, denote the inputs by $\{z_i; 0 \leq i < \infty\}$. Next, recursively define a sequence of sets of variables $\{M_i\}$ according to the following rule:

$$M_0 := \{z_0\}$$

$$M_{i+1} := \{A_0(M_i), z_{i+1}\}$$

Thus, each set contains one new inputs of the MCN and all the immediate successors of the preceding set. The sets M_i are clearly disjoint, and, in view of the local-finiteness property, each M_i set is finite. Moreover, every variable of the MCN is included in some M_i set, because every variable is either a global input or a finite successor of some global input. Thus, the cascade

$$M_0 * M_1 * M_2 * \dots$$

is, in fact, a representation of the network as a cascade of finite (disjoint) subnetworks. Each M_i set is finite, hence has an execution with a finite number of levels. If we replace each M_i by its execution, we obtain a refinement of the previous representation, viz.,

$$S_{00} * S_{01} * \dots * S_{10} * S_{11} * \dots * \dots$$

where $\{S_{ij}\}$ are the levels corresponding to the set M_i . Since each S_{ij} is finite, this is clearly an execution of the global MCN.

APPENDIX B
ADMISSIBLE ARCHITECTURES

A composition of processors is called admissible if the following three conditions are satisfied:

- (i) There are no dangling inputs or outputs.
- (ii) There are no directed cycles.
- (iii) The architecture is structurally finite.

Each of the processors comprising an architecture can itself be a composition of more elementary processors. The hierarchical nature of the admissibility property implies the following result.

Theorem B.1

An admissible composition of admissible architectures is itself an admissible architecture.

Proof:

The theorem states that the three properties making up admissibility should be exhibited by the composite architecture, if they were exhibited by each of the subnetworks.

- (i) The composite architecture has no dangling terminals, because every terminal is connected to some subnetwork (by admissibility of the composition) and no subnetwork has dangling terminals (by admissibility of the subnetworks).
- (ii) The composite architecture has no cycles because neither the subnetwork nor the composition has cycles.

(iii) Structural finiteness is made up of the three following properties: Local finiteness, finite ancestries, and countability of connected components. Local finiteness is inherited by the composite architecture because composition does not change the number of inputs/outputs of processors within each subnetwork. To prove that the finite ancestry property is also inherited by the composite architecture it will be sufficient to consider a single variable x . Suppose that x belongs to some subnetwork \mathcal{G}_i . By the admissibility of the composition, \mathcal{G}_i has a finite number of ancestor subnetworks. The ancestry of x is obtained by tracing back the ancestry relation through the finite collection of subnetworks $a(\mathcal{G}_i)$. And since each subnetwork is admissible, the portion of $a(x)$ within each ancestor of \mathcal{G}_i is also finite, hence $a(x)$ itself is finite. Finally, an admissible composition has a countable number of subnetworks (see Theorem 2.1) and each subnetwork has, by assumption, a countable number of connected components. Hence, the total number of connected components in the composite network is countable, too.

APPENDIX C
PROOF OF THEOREM 2.3
MINIMAL EXECUTIONS OF FINITE MCNs

Every execution determines a numbering $E()$ of the variables of an MCN, viz.,

$$x \in S_i \leftrightarrow E(x) = i$$

This integer valued function satisfies the inequality (see Section 3.1)

$$E(x) - 1 \geq \max_y \{E(y); y \in \alpha(x)\} \quad (C.1)$$

Every finite directed acyclic graph has a unique numbering $\hat{E}()$ of its arcs (or equivalently of its vertices) that satisfies the equality

$$\hat{E}(x) - 1 = \max_y \{\hat{E}(y); y \in \alpha(x)\} \quad (C.2)$$

This well-known result (see, e.g., [14]) implies that every finite executable MCN has a unique execution that satisfies (C.2). We shall call this unique execution minimal for reasons that will become clear in the sequel.

Let $E()$ be an arbitrary non-minimal execution. Then, there exists some variable x for which the strict inequality

$$E(x) - 1 > \max_y \{E(y); y \in \alpha(x)\}$$

holds. This means that x is evaluated several steps after all its ancestors became available. Consequently, the numbering of x can be modified to $1 + \max_y \{E(y); y \in \alpha(x)\}$ without violating the precedence

relation. We shall refer in the sequel to this modification as an elementary shift.

Each execution is a series-parallel combination and consequently has a well defined input-output map. Elementary shifts replace expressions of the form $e * e * \dots * p$ by expressions of the form $p * e * \dots * e$ (see Figure C-1). If the physically justifiable identity

$$p * e = e * p \quad (C.3)$$

is added as an axiom of the theory of MCNs (see Appendix D), we conclude that input-output maps remain invariant under elementary shifts. This leads to the following result.

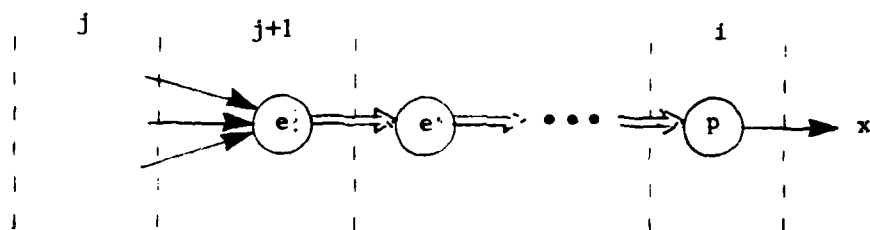
Theorem C.1

Every execution $E()$ of a finite MCN can be transformed by a finite number of elementary shifts into the unique minimal execution.

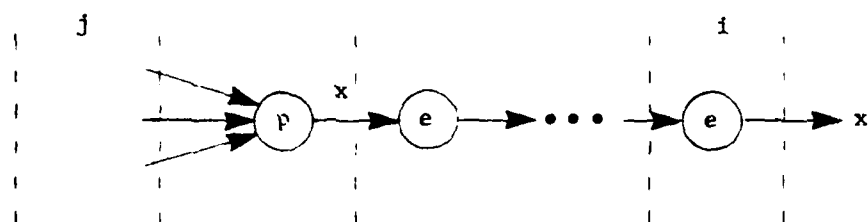
Proof:

The minimal execution $E()$ is constructed by the following simple algorithm (see, e.g., [14]):

- (i) Put all the global inputs of the MCN in \hat{S}_0 .
- (ii) For $i = 0, 1, 2, \dots$ put all the immediate successors of members of \hat{S}_i in \hat{S}_{i+1} .



a. Before the Shift



b. After the Shift

Figure C-1. The Effect of an Elementary Shift.

$$E(x) = i; \max_y \{E(y); y \in a(x)\} = j.$$

Now, if $E()$ is a nonminimal execution we transform it into $\hat{E}()$ by the following rule:

For $i = 0, 1, 2, \dots$ shift all members
of \hat{S}_i from $E(x)$ to $\hat{E}(x) = i$.

Since the MCN is finite, a finite number of shifts will transform $E()$ into $\hat{E}()$. Notice that each variable is shifted exactly once. Also notice that by its construction, the number $\hat{E}(x)$ is equal to the lengths of the shortest path connecting x to some global input. Hence, $\hat{E}(x)$ cannot be further reduced.

Corollary C.1.1

The minimal execution $\hat{E}()$ satisfies $\hat{E}(x) \leq E(x)$ for every variable x and for every execution $E()$.

Corollary C.1.2

A finite executable MCN has a unique well-defined input-output map. This is so because all executions define the same map, by Theorem C.1.

Proof of Theorem 2.3

Corollary C.1.2 establishes the theorem for finite MCNs. For infinite networks it will be sufficient to prove that for every execution $E()$ and for every variable x the map from global inputs to x is unique and does not depend upon the choice of execution. However, $E()$ induces some execution on the finite MCN corresponding to $a(x)$, the finite ancestry of x . Therefore, the map from inputs to x coincides, for every choice of $E()$, with the unique map determined by the minimal execution on $a(x)$.

It is interesting to notice that an infinite MCN does not have, in general, a minimal execution. The construction procedure described in the proof of Theorem C.1 is still valid, but \hat{S}_1 are, in general, infinite and do not determine a valid execution.

APPENDIX D
ELEMENTARY EQUIVALENCE TRANSFORMATIONS

The general theory of MCNs does not involve any specific assumptions about the properties of the processor maps $\{f_p\}$. Consequently, there are only a few equivalence transformations that are still valid in this general framework. Most equivalence transformations used with block-diagrams and signal-flow-graphs involve linearity assumptions and do not hold for general nonlinear maps.

Two basic maps, the identity map e and the split map s can be used in conjunction with any MCN manipulation. The identity map leaves its input variables unchanged, viz.,

$$e(x) = x$$

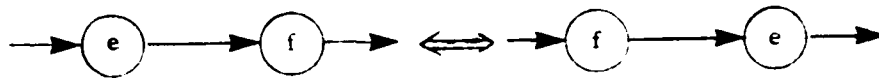
The split map duplicates input variables, viz.,

$$s(x) = (x, x)$$

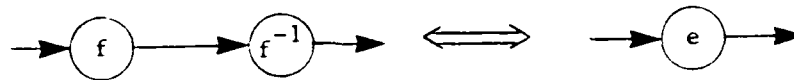
It is possible, of course, to have more than two copies of the same variable, either by introducing a split processor with several outputs, or by using several two-output split processors.

The properties of the identity and split processors give rise to several elementary equivalence transformations (Figure D-1):

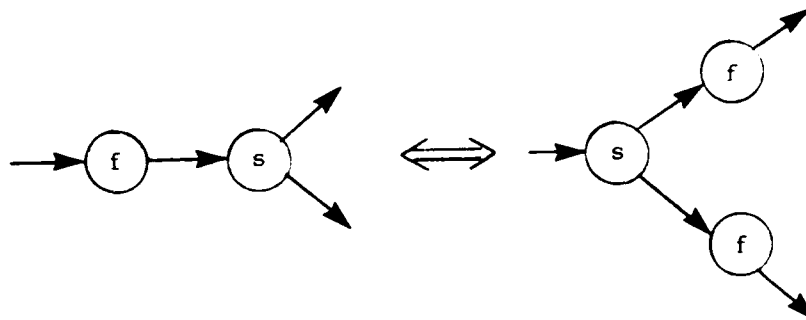
- (a) The identity commutes with any other processor f .
- (b) The cascade of a processor f and its inverse f^{-1} can be replaced by an identity processor, provided the processor f has an inverse.
- (c) The split processor 'commutes' with any processor f .
- (d) Any processor f with two outputs can be replaced by a composition of a split processor and two single output processors f_1, f_2 . The processors f_1, f_2 correspond to the maps from inputs to each of the two outputs, respectively.



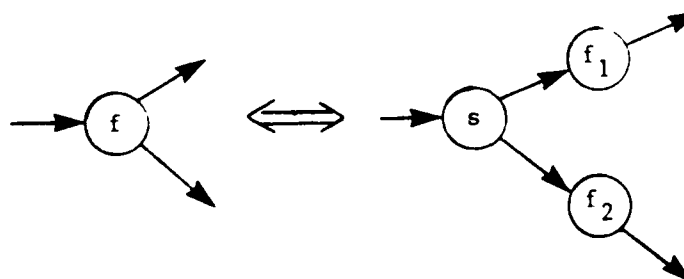
a. Commutativity of the Identity



b. The Inverse Processor



c. Commutativity of the Split



d. Splitting of Multivariable Outputs

Figure D-1. Elementary Equivalence Transformations

APPENDIX E

ANALYSIS OF MATRIX MULTIPLIERS

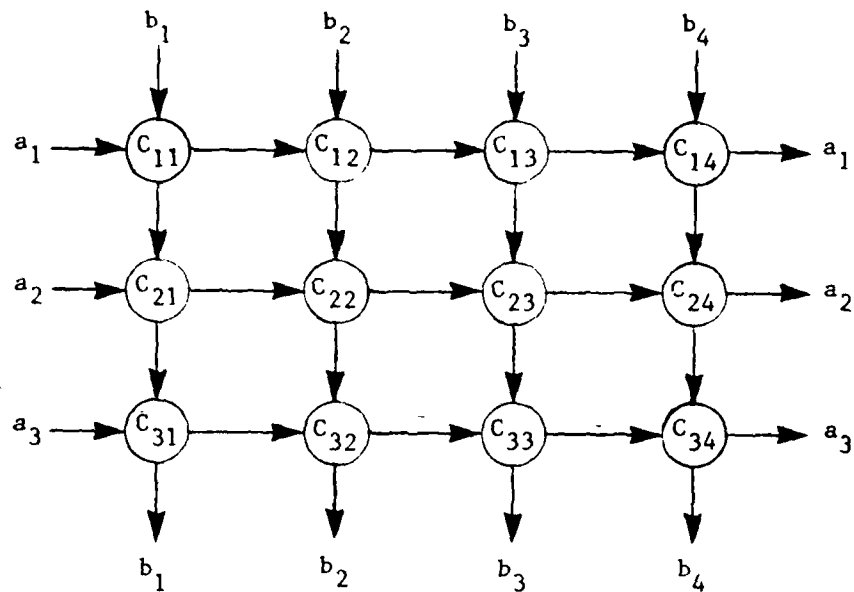
The multiplication of two matrices involves the computation of inner products between every row of one matrix and every column of the other one. To emphasize this interpretation we shall consider in the sequel the product

$$C := A^* B$$

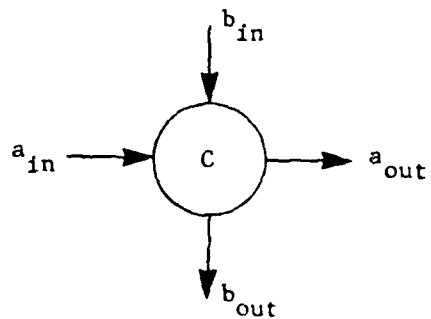
so that the inner products are between columns of A and columns of B . In fact, C_{ij} is precisely the inner product between the i -th column of A and the j -th column of B . Consequently, we can compute the product by feeding the columns of A, B , which we denote by a_i, b_j , into the MCN of Figure E-1. Each input is a column vector which is propagated without modification through the network. The a, b inputs of each processor propagate through without modification and the inner product of the two input vectors is computed inside the processor. This multichannel configuration can be further decomposed by observing that the inner products can be computed recursively, i.e., if $c := a^* b$ where $a = \{a_i\}$, $b = \{\beta_i\}$ are column vectors of length N , then $c = c_N$ where

$$c_i = c_{i-1} + a_i \beta_i, \quad c_0 = 0$$

Thus, every single processor in Figure E-1 is, in fact, a cascade of basic 'multiply and add' processors (Figure E-2). When this decomposition is combined with the architecture of Figure E-1, we obtain the MCN for matrix multiplication. Figure E-3 displays a side view of this 3-D network whose top view is shown in Figure E-1. The complete MCN consists of N horizontal layers such as in Figure E-1 arranged in a vertical stack. Equivalently, we may say the MCN consists of three vertical layers such as in Figure E-3 arranged behind each other. It is important to notice that



a. The Complete Network



$$a_{out} = a_{in}, b_{out} = b_{in}, c = a_{in}^* b_{in}$$

b. A Single Processor

Figure E-1. A Basic Matrix Multiplier

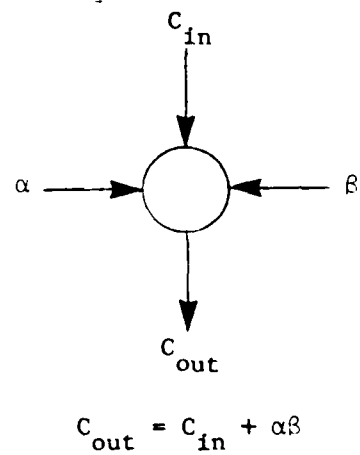
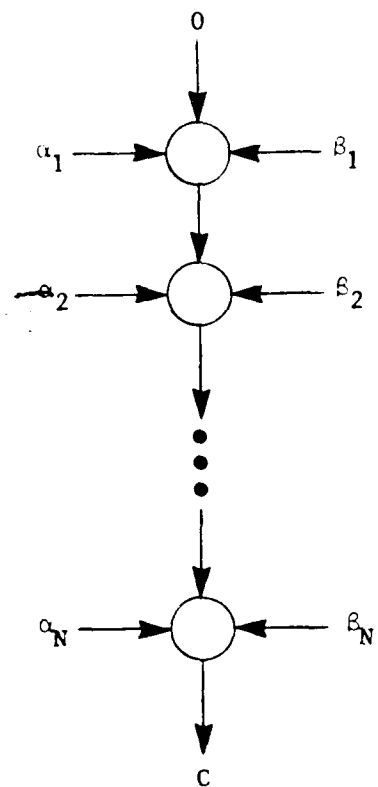


Figure E-2. A Basic Inner Product Array

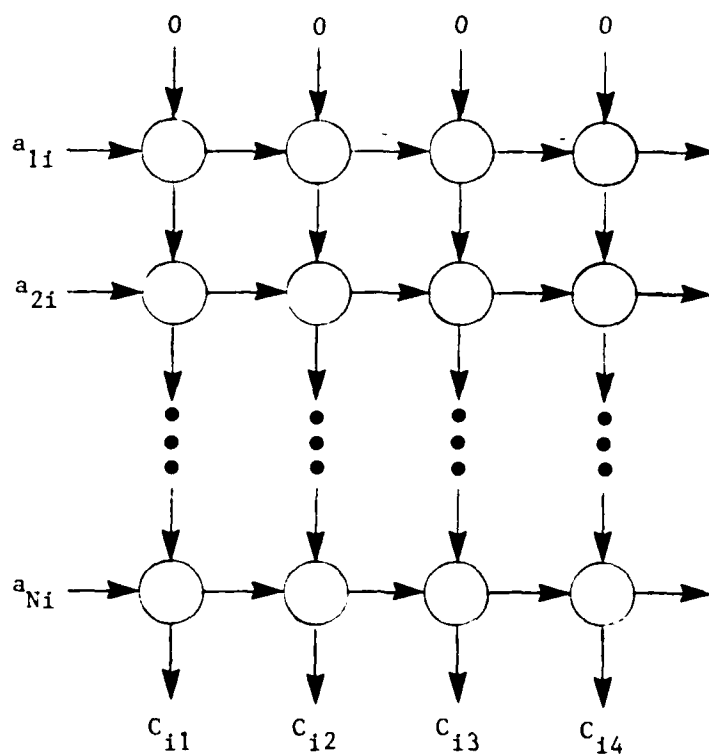


Figure E-3. The MCN of Matrix Multiplication
(side view shows i -th vertical layer)

the direction of the C-paths can be either from top to bottom, as shown in Figure E-3, or from bottom to top. This is a consequence of the commutativity and associativity of addition, viz.,

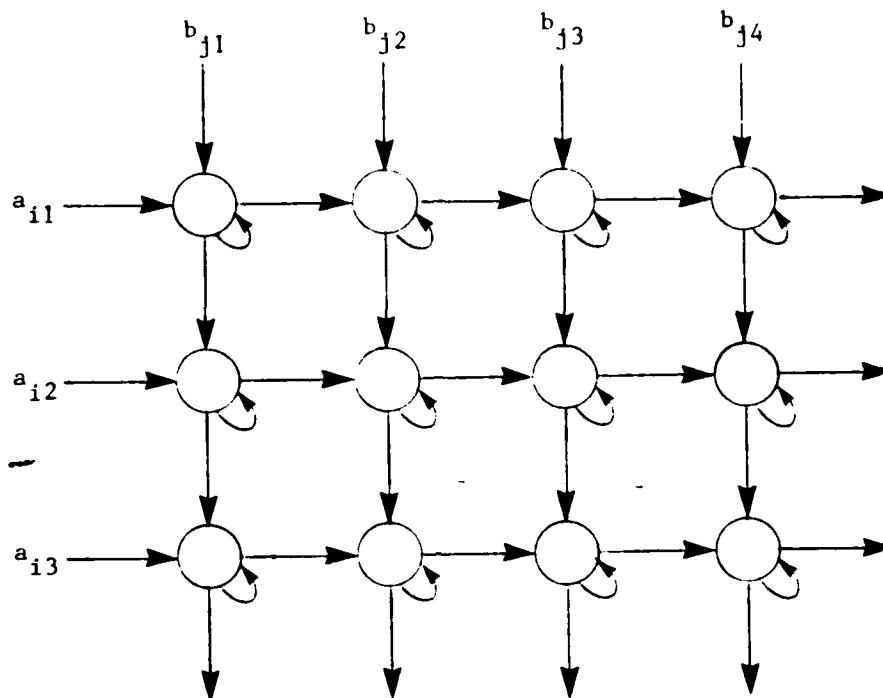
$$\sum_{i=1}^N a_i \beta_i = \sum_{i=N}^1 a_i \beta_i$$

This means that there are two distinct MCNs that correspond to matrix multiplication and they differ only by the direction of the C-paths.

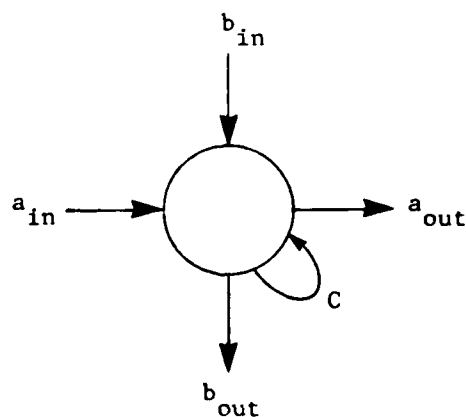
Every architecture for matrix multiplication is equivalent to the MCN of Figure E-3. The various architectures are obtained by imposing additional constraints upon the matrices (i.e., bandedness) and rearranging the resulting reduced MCN as a space-time diagram. The corresponding self-timed block-diagram follows immediately from this rearrangement.

The matrix multiplier of S.Y. Kung [7] is obtained by interpreting the vertical dimension in Figure E-3 as 'time.' Since vertical arrows correspond to local storage, the resulting block-diagram is described in Figure E-4 (notice the similarity with E-1). The elements of each column vector a_i, b_j are fed sequentially into the array and each processor has a self-loop which computes the inner-product $c_{ij} = a_i^* b_j$ recursively in time.

The matrix multiplier of S. Rao [10] is designed for a banded B matrix. It will be sufficient to analyze it for a single column of A, say a_i . The MCN of Figure E-3 now has only one vertical layer, and many processors in this layer have zero inputs and can be eliminated. The resulting reduced MCN is shown in Figure E-5a. Dummy processors, shown in broken line, were added to emphasize the tridiagonal nature of the MCN. A self-timed block-diagram (Figure E-5b) is obtained by considering the diagonal axis as 'time.' It consists of a linear array of identical processors, one for each nonzero diagonal of the banded matrix B. The elements of B are fed into the array by diagonals. The elements of A, C are handled by columns: Every column of A produces a row of C and requires a linear array as in Figure E-5b. It is interesting to notice that the input interval of this matrix multiplier is $\tau_c + \tau_a$ where τ_c is the



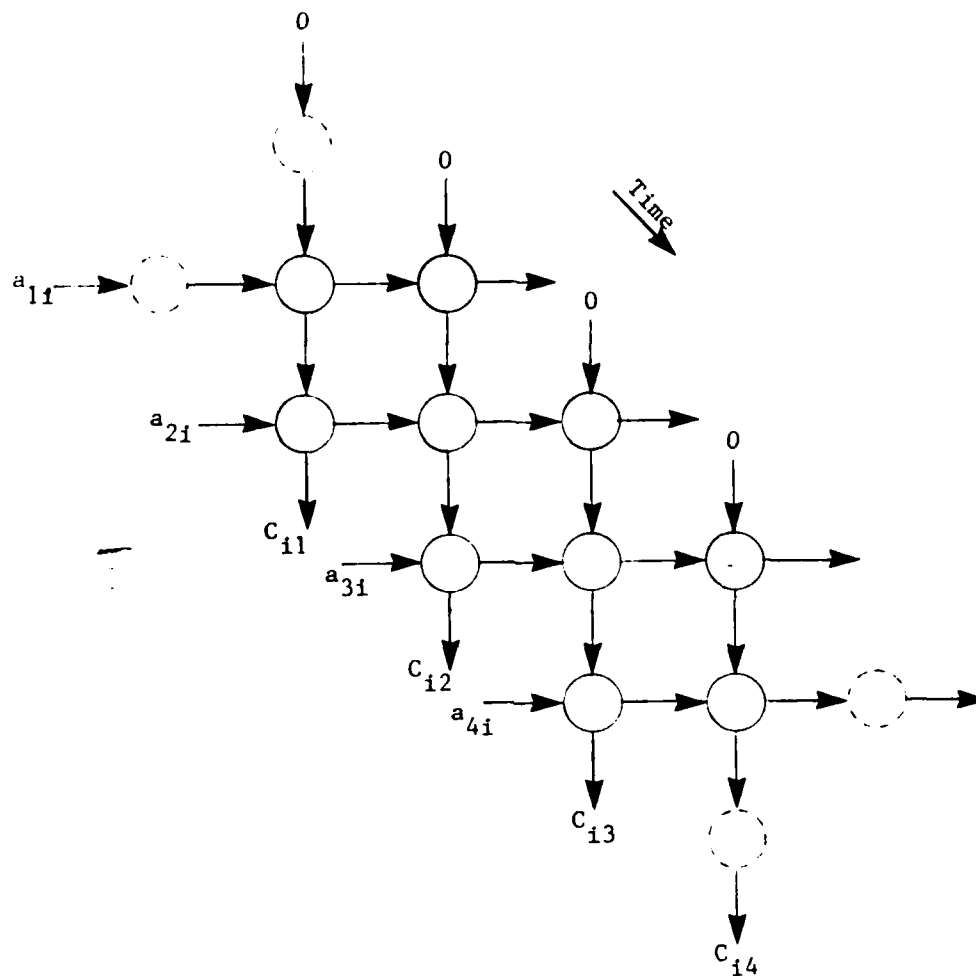
a. Self-Time Block-Diagram



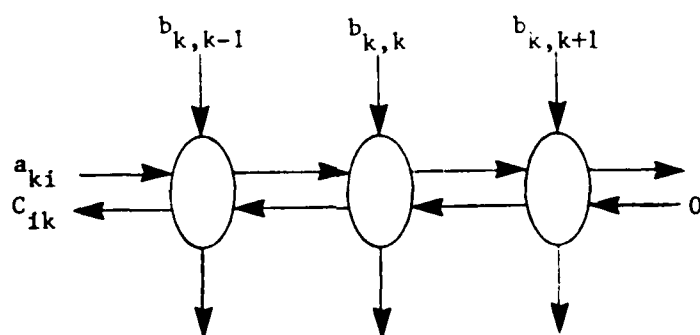
$$a_{out} = a_{in}, b_{out} = b_{in}, C_{new} = C_{stored} + a_{in} b_{in}$$

b. Single Processor

Figure E-4. The Matrix Multiplier of S.Y. Kung



a. Reduced MCN

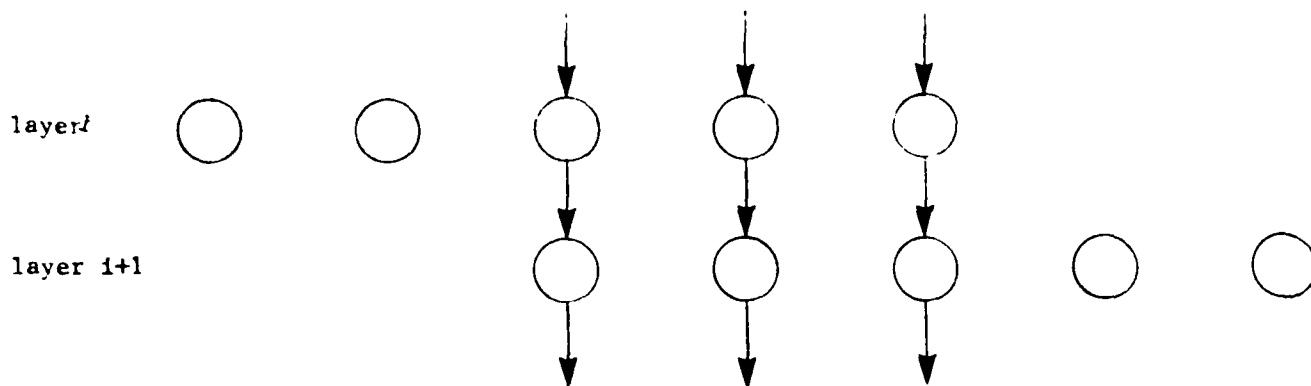


b. Self-Timed Block-Diagram

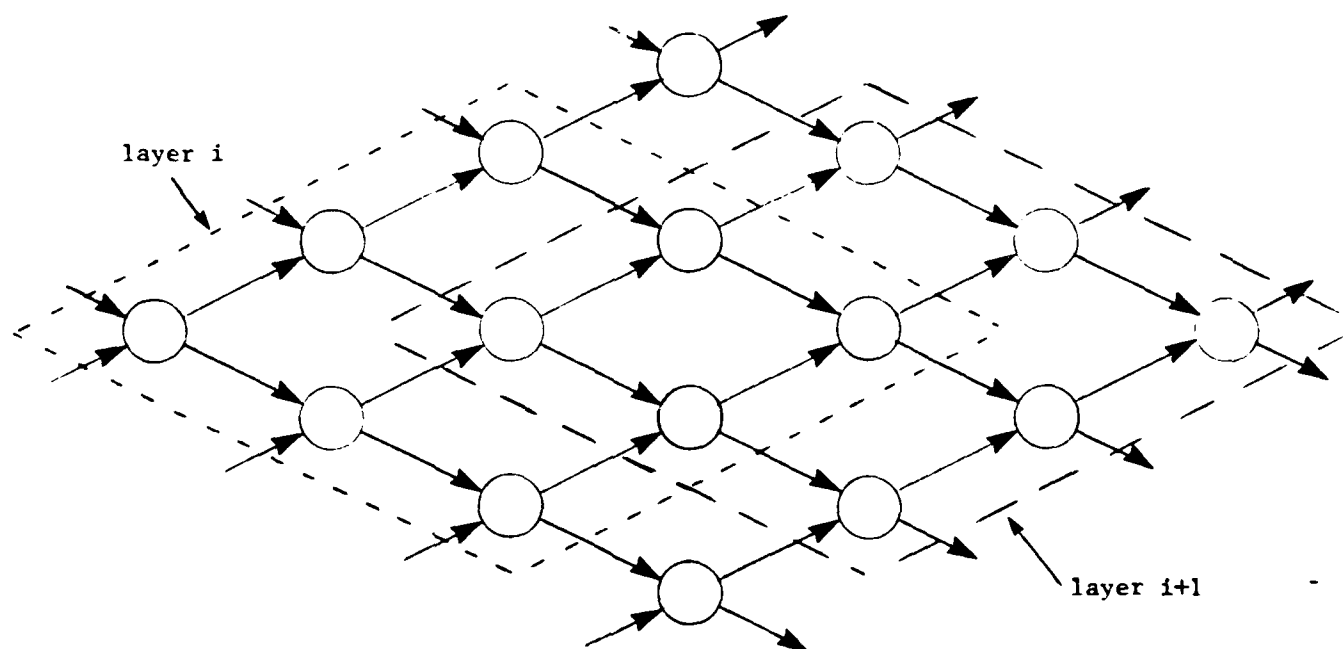
Figure E-5. The Matrix Multiplier of S. K. Rao

time required to compute 'c' and τ_a is the time required to propagate 'a' through one processor. When the direction of the C-path or, equivalently, of the A-path, is reversed the input interval becomes $\tau_c - \tau_a$. Since $\tau_a \ll \tau_c$ the two networks differ only slightly in their throughput. However, we shall presently encounter another example where the reversal of the C-path results in a large increase in throughput.

The matrix multiplier of H.T. Kung is designed for banded A, B matrices. This means that the active processors in the non-reduced MCN of Figures E-1 and E-3 are located within a parallelepiped aligned with one of the main diagonals of the rectangular prism representing the non-reduced MCN. A simple illustration of the reduced MCN is obtained by considering two adjacent horizontal layers (Figure E-6). When we slide the horizontal layers so that they overlap, the resulting network corresponds to H.T. Kung's multiplier (Figure E-7). This network clearly has an input interval of $\tau_c + 2\tau_a$. However, if we reverse the C-path we obtain the configuration of Weiser and Davis [4] (Figure E-8) which has an input interval of $|\tau_c - 2\tau_a|$. The difference between the two multipliers is significant when they are implemented by single rate systolic arrays. In this case $\tau_c = \tau_a = \tau$ so that the former network has an input interval of 3τ while the latter has an input interval of τ !

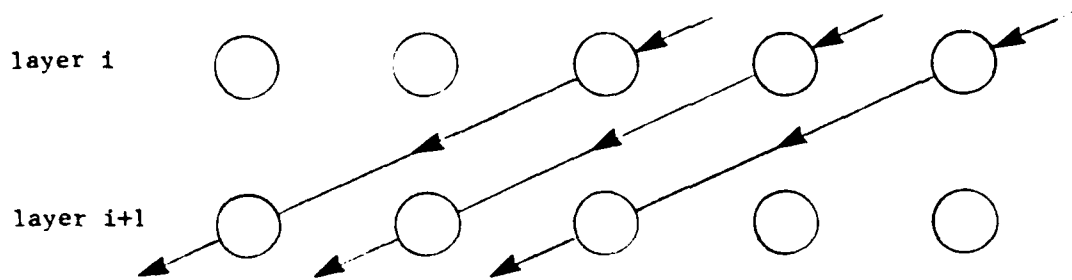


a. Side View

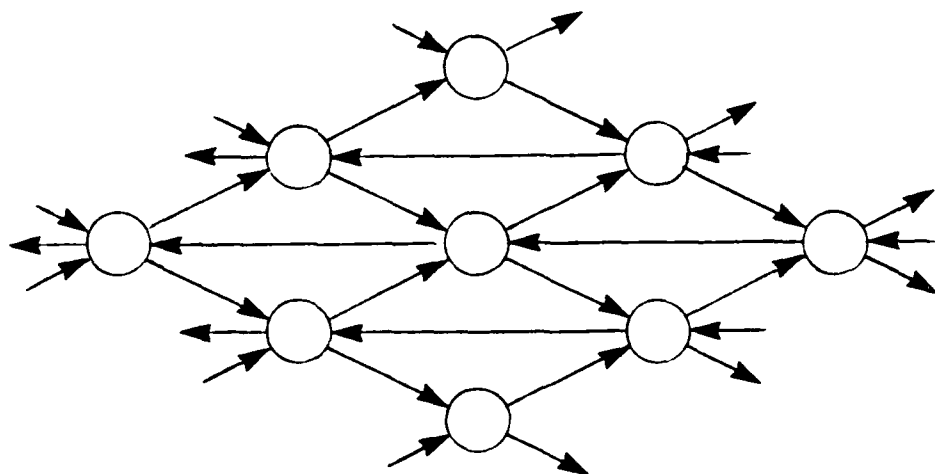


b. Top View

Figure E-6. The Reduced MCN for Banded Matrix Multiplication

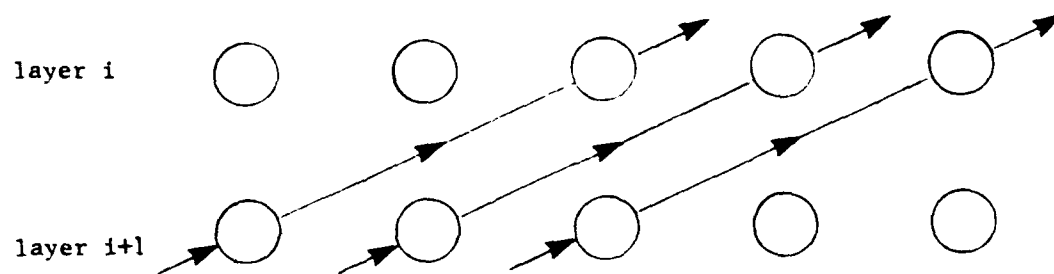


a. Side View

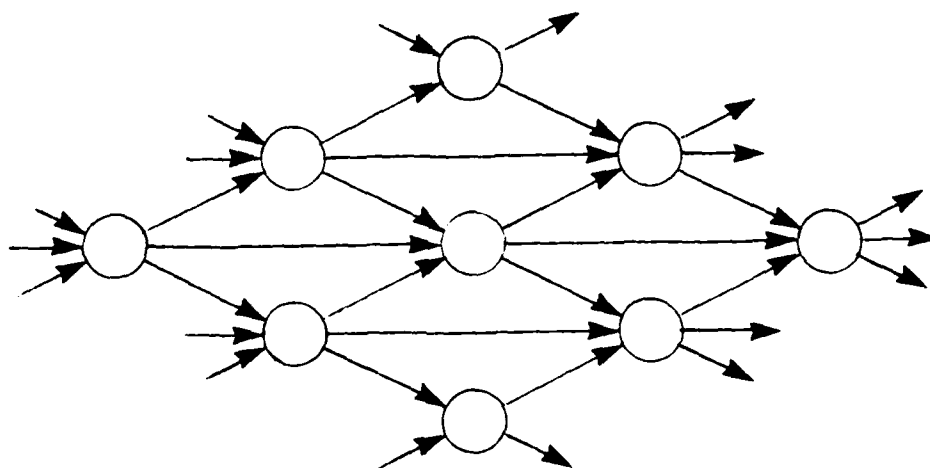


b. Top View

Figure E-7. The Matrix Multiplier of H.T. Kung



a. Side View



b. Top View

Figure E-8. The Matrix Multiplier of Weiser and Davis

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